Implementation and Analysis of Date Fruit Grading Framework using Logistic Regression Classifier

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***Abstract*—Date fruit grading plays a crucial role in ensuring quality assurance, market value optimization, and automated post-harvest processing in the agri-food industry. This paper presents the implementation and analysis of a Date Fruit Grading Framework using a Logistic Regression classifier, focusing on multi-class classification of seven commercially significant date varieties, namely Berhi, Deglet, Dokol, Iraqi, Rotana, Safavi, and Sogay. The proposed framework utilizes discriminative feature representations extracted from the dataset and evaluates the effectiveness of Logistic Regression against other conventional machine learning classifiers. Experimental results demonstrate that the Logistic Regression model achieves an overall classification accuracy of 91.11% with a mean squared error (MSE) of 1.10, outperforming Support Vector Machine, XGBoost, KNN, and Random Forest, Decision Tree, and AdaBoost classifiers. Detailed performance analysis reveals strong class-wise precision, recall, and F1-score values, with a weighted average precision, recall, and F1-score of 0.91, indicating consistent predictive capability across all date varieties. The confusion matrix analysis further confirms robust inter-class separability, particularly for Dokol, Safavi, and Rotana classes, which exhibit minimal misclassification. These results validate the suitability of Logistic Regression as a reliable and computationally efficient baseline classifier for automated date fruit grading applications. The proposed framework can be effectively deployed in real-time quality inspection systems to support intelligent agricultural decision-making and scalable grading solutions.**

***Index Terms*—Automated grading, Date fruit classification, Logistic regression, Machine learning, multi-class classification, Quality assessment.**

I. INTRODUCTION

Date fruit (Phoenix dactylifera L.) is one of the most nutritionally rich and economically valuable horticultural crops cultivated extensively across arid and semi-arid regions of the world. The commercial value of date fruits is highly dependent on their variety, maturity level, texture, and visual quality attributes, which directly influence consumer acceptance, export standards, and pricing. As a result, accurate grading and classification of date fruit varieties is a critical post-harvest operation in the agri-food supply chain. Traditional grading methods rely heavily on manual inspection by skilled labour, which is often time-consuming, subjective, error-prone, and difficult to scale for large-volume processing environments. Recent advancements in machine learning and intelligent data-driven systems have opened new possibilities for automating agricultural quality assessment tasks. Machine learning-based classification models are capable of learning complex decision boundaries from data and can provide consistent, repeatable, and objective grading outcomes. Among these, multi-class classification frameworks are particularly important for date fruit grading, as commercial datasets often contain multiple varieties with overlapping visual and textural characteristics. Developing a reliable and computationally efficient classifier that can accurately distinguish among such varieties remains a significant research challenge. While deep learning approaches have shown promising performance in image-based agricultural applications, they often require large annotated datasets, high computational resources, and extended training times, which may not be feasible for low-cost or real-time deployment scenarios. In contrast, traditional machine learning algorithms, when combined with well-engineered feature representations, can offer competitive performance with lower computational complexity and greater interpretability. Among these algorithms, Logistic Regression has emerged as a robust discriminative classifier, particularly suited for multi-class problems due to its probabilistic formulation, fast convergence, and strong generalization ability.

Logistic Regression operates by modelling the posterior probability of class membership and learning optimal decision boundaries through maximum likelihood estimation. Its linear decision structure, coupled with regularization techniques, allows effective handling of class overlap while minimizing overfitting. Despite its simplicity, Logistic Regression has demonstrated strong performance in various agricultural classification tasks, including crop disease detection, fruit quality assessment, and varietal discrimination. However, its potential for automated date fruit grading across multiple varieties has not been sufficiently explored in existing literature. In this context, the present study proposes an automated Date Fruit Grading Framework using a Logistic Regression classifier, targeting the classification of seven commercially significant date fruit varieties such as Berhi, Deglet, Dokol, Iraqi, Rotana, Safavi, and Sogay. The proposed framework systematically evaluates the discriminative capability of Logistic Regression and compares its performance with several widely used machine learning classifiers, including Support Vector Machine, Random Forest, Decision Tree, KNN, XGBoost, and AdaBoost. The evaluation is conducted using standard performance metrics such as accuracy, precision, recall, F1-score, mean squared error, and confusion matrix analysis to ensure a comprehensive assessment. The experimental results demonstrate that the Logistic Regression model achieves superior classification accuracy and balanced class-wise performance compared to the other evaluated models, confirming its effectiveness for multi-class date fruit grading. The findings highlight that a well-designed traditional machine learning approach can serve as a reliable, interpretable, and computationally efficient solution for real-time agricultural quality inspection systems. The proposed framework has the potential to support intelligent decision-making in post-harvest processing, reduce dependency on manual grading, and contribute toward scalable and cost-effective smart agriculture applications.

II. REVIEW OF LITERATURE

Early studies on automated date fruit grading and classification primarily relied on handcrafted image processing techniques and conventional pattern recognition methods. Initial efforts demonstrated the feasibility of grading using shape, texture, and external morphological features extracted from captured images [1], [2]. Subsequent research expanded these approaches by incorporating statistical image analysis and machine learning classifiers for varietal identification and quality assessment [3]. As research progressed, hybrid models combining image features with convolutional neural networks and ensemble strategies began to emerge, showing improved robustness and classification accuracy [4], [5]. Parallel developments explored advanced learning paradigms such as reinforcement learning assisted fusion models and multivariate classification frameworks to address grading complexity [6], while broader agricultural applications validated the effectiveness of machine learning for fruit and vegetable detection and sorting [7]. Logistic regression-based maturity classification and quality assessment techniques were also explored in related fruit domains [8], [9], alongside CNN based transfer learning methods for intelligent fruit quality evaluation [10], [11].

More recent studies have increasingly focused on deep learning driven approaches for date fruit classification, emphasizing CNN architectures, transfer learning, and comparative classifier analysis. Researchers investigated a wide range of classifiers to benchmark performance across different datasets and feature representations [12], while deep transfer learning models demonstrated strong generalization for varietal classification [13]. Ensemble machine learning frameworks integrating optimized feature selection techniques further improved multi-class classification performance [14], and dimensionality reduction workflows were proposed to enhance recognition accuracy while reducing computational complexity [15]. Hybrid deep learning systems combining CNNs with discriminant correlation analysis were introduced for automated sorting applications [16], building upon earlier deep learning-based sorting methodologies [17]. Transfer learning-based classification systems continued to show promising results across diverse datasets [18], while CNN models targeting surface quality assessment highlighted the effectiveness of deep features in identifying subtle visual defects [19]. The integration of explainable artificial intelligence further enhanced model transparency and trustworthiness in classification decisions [20].

Recent contributions emphasize dataset expansion, real-time applicability, and system level optimization. Novel Logistic Regression based intelligent classification systems utilizing newly developed datasets have been proposed to improve robustness and practical deployment [21], while deep learning techniques using captured images demonstrated effectiveness in real-world quality grading scenarios [22]. Feature selection driven deep learning architectures were explored to optimize genetic variety classification [23], building upon earlier deep learning-based grading techniques applied to novel datasets [24] and foundational pattern recognition systems [25]. Classical shape and texture based grading methods remain relevant as benchmarks [26], alongside color- and geometry-based classification algorithms [27]. Deep CNN architectures continue to dominate recent research [28], supported by early deep learning based automated sorting systems [29]. Comparative analyses between CNN feature extraction and conventional machine learning models further clarified performance trade-offs [30], while hardware-software co-design approaches addressed implementation efficiency [31]. Supplementary deep learning-based CNN classification studies [32], advanced CNN models for varietal identification [33], and traditional image processing techniques such as bit-plane slicing [34] collectively illustrate the steady evolution from handcrafted feature-based methods to intelligent, explainable, and scalable deep learning systems for automated date fruit grading and classification.

III. DATASET

The dataset shown in Table. 1, was organized to support multi-class date fruit grading across seven varieties: DOKOL, SAFAVI, ROTANA, DEGLET, SOGAY, IRAQI, and BERHI. Initially, the dataset was inspected to understand the class distribution and confirm the availability of sufficient samples per category. The observed sample counts indicated in Fig. 1, were DOKOL (204), SAFAVI (199), ROTANA (166), DEGLET (98), SOGAY (94), IRAQI (72), and BERHI (65), resulting in a total of 898 samples. The corresponding class-count visualization confirms a moderate class imbalance, where DOKOL and SAFAVI dominate the dataset, while BERHI and IRAQI contain comparatively fewer instances. This imbalance is important because it can bias a classifier toward majority classes if not handled carefully during training and evaluation.After confirming class availability, the dataset was prepared by selecting the predictor features (input attributes from the CSV) and the target label (the “Class” column).

Table 1 Dataset distribution for ANN model Evaluation

	AREA	PERIMETER	MINOR_AXIS	EQDIASQ	ROUNDNESS	SHAPE	MeanRR	MeanRG	StdDevRB	SkewRG	EntropyRG	ALLdaub4RR
0	422163	2378.908	645.6693	733.1539	0.9374	0.0020	117.4466	109.9085	30.1230	-0.0114	-50714214400	58.7255
1	338136	2085.144	595.2073	656.1464	0.9773	0.0021	100.0578	105.6314	28.1229	0.1349	-37462601728	50.0259
2	526843	2647.394	715.3638	819.0222	0.9446	0.0018	130.9558	118.5703	33.9053	-0.1059	-74738221056	65.4772
3	416063	2351.210	645.2988	727.8378	0.9458	0.0020	86.7798	88.2531	30.3955	1.2917	-32060925952	43.3900
4	347562	2160.354	582.8359	665.2291	0.9358	0.0022	105.5484	101.8132	27.1741	0.2101	-35980042240	52.7743

Basic cleaning steps were applied, including checking for missing values, removing duplicates (if any), and ensuring that all predictor columns were stored as numeric types suitable for machine learning models. Since the class labels are categorical strings (e.g., DOKOL, SAFAVI), they were converted into numeric form using label encoding so that the classifier could learn a mapping between feature patterns and class indices.Fuerther, the dataset was partitioned into training and testing subsets using a stratified split, ensuring that each date variety retained approximately the same proportion in both sets. Stratification is especially important here due to the unequal class counts. Because Logistic Regression is sensitive to feature scale when features have different ranges, the numeric features were standardized (for example, using z-score normalization) based only on the training data statistics and then applied consistently to the test set to prevent data leakage. Lastly the prepared dataset (encoded labels + scaled features + stratified split) was used for model training and evaluation, ensuring that performance metrics such as precision, recall, F1-score, and the confusion matrix reflect a fair assessment across all seven date fruit classes.

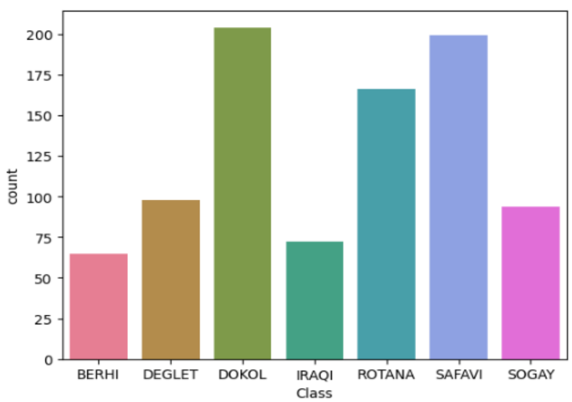

Figure 1 The dataset to support multi-class date fruit grading

IV. EXPERIMENTATION

The proposed methodology shown in Fig. 2, for automated date fruit grading is designed to accurately classify multiple date fruit varieties using a Logistic Regression based multi-class classification framework.

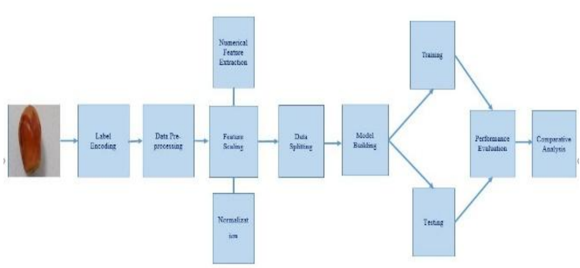

Figure 2 The proposed methodology

The overall workflow consists of data preprocessing, feature normalization, model formulation, training, and performance evaluation. Each stage is carefully structured to ensure robustness, generalization capability, and fair comparison with other machine learning classifiers.

A. Data Preprocessing and Label Encoding

The dataset comprises multiple numeric predictor attributes representing measurable characteristics of date fruits, along with a categorical class label indicating the fruit variety. As Logistic Regression operates on numerical inputs, all categorical class labels were transformed into numeric form using label encoding, where each date variety was assigned a unique integer identifier.

Let the dataset be

$$D = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots \dots \dots \dots (x_i, y_i)\} \quad (1)$$

Prior to model training, the dataset was inspected for missing values, inconsistencies, and duplicate records, and necessary cleaning operations were performed to maintain data integrity.

B. Feature Scaling and Normalization

Feature scaling plays a critical role in Logistic Regression, as the algorithm is sensitive to variations in feature magnitude. To ensure uniform contribution of all input features during optimization, standardization was applied to the dataset. Each feature was transformed to have zero mean and unit variance using statistics computed from the training subset. The same scaling parameters were then applied to the test subset to prevent data leakage and ensure consistency during evaluation.

C. Multi-Class Logistic Regression Model Formulation

Logistic Regression is inherently a binary classifier; therefore, a multi-class extension was employed to handle the seven-class date fruit grading problem. The one-vs-rest (OvR) strategy was adopted, in which separate binary classifiers were trained for each date variety by distinguishing one class from all others. The probability of class membership was modelled using the softmax function, enabling the estimation of posterior probabilities across all classes. Model parameters were learned by maximizing the log-likelihood function using iterative optimization techniques. To prevent overfitting and improve generalization, regularization was incorporated into the model formulation. The regularization term penalizes excessively large weight values, ensuring stable decision boundaries even in the presence of overlapping feature distributions among different date varieties.

D. Model Training and Data Splitting Strategy

The dataset was partitioned into training and testing sets using a stratified sampling approach, ensuring that each date fruit class was proportionally represented in both subsets.

The dataset D is divided into two disjoint subsets:

i. Training Set D_{train} used to build the regression model
ii. Testing Set D_{test} used to evaluate generalization performance.

If the splitting ratio 80:20, the 80N samples are used for training and 0.2N for testing, mathematically,

$D_{train} \cup D_{test} = D, \ D_{train} \cap D_{test} = 0$

Random sampling ensures that both subsets preserve the sane statistical distribution of features and target values. Stratification is particularly important in this study due to moderate class imbalance across varieties. The Logistic Regression model was trained exclusively on the training data, while the test data was reserved for unbiased performance evaluation. Model convergence was achieved through iterative optimization until the loss function reached a stable minimum.

E. Performance Evaluation Metrics

Model parameters are estimated by minimizing the cross-entropy loss

$C = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic} \log P(y_i = \{c|x_i\})$ (2)

This loss measures the discrepancy between predicted probabilities and true class labels

Model Evalution (Accuracy)

Classification accuracy is computed as:

$Accuracy = \frac{1}{N}\sum_{i=1}^{N}(\overline{y_i} = y_i)$ (3)

Where I (.) is the indicator function

V. RESULT AND DISCUSSION

The trained model was evaluated using a comprehensive set of performance metrics suitable for multi-class classification tasks. These include classification accuracy, precision, recall, and F1-score, computed on a per-class basis as well as macro-averaged and weighted averaged forms to account for class imbalance. The quantitative evaluation (Table. 2) using precision, recall, and F1-score further confirms the effectiveness of the proposed multiclass logistic regression classifier. High-performing classes such as class DOKOL and SAFAVI achieve precision and recall values above 0.97, resulting in F1-scores close to unity, which indicates excellent class separability and highly consistent predictions. Classes BERHI, IRAQI, and ROTANA demonstrate balanced precision–recall trade-offs with F1-scores ranging from 0.86 to 0.94, reflecting stable and reliable classification performance. Slightly lower scores observed for classes DEGLET and SOGAY (F1-scores ≈ 0.77–0.79) suggest partial overlap in feature space with neighbouring classes, consistent with the misclassification patterns observed in the confusion matrix. The overall classification accuracy of 0.91, along with macro-averaged and weighted F1-scores of 0.88 and 0.91, respectively, highlights the robustness of the model across both balanced and imbalanced class distributions, validating its suitability for automated date fruit grading applications.

Table 2 The quantitative evaluation of the proposed multiclass logistic regression classifier

	precision	recall	f1-score	support
0	0.94	0.80	0.86	20
1	0.79	0.76	0.77	29
2	0.97	0.97	0.97	61
3	0.87	0.91	0.89	22
4	0.92	0.96	0.94	50
5	0.97	0.98	0.98	60
6	0.79	0.79	0.79	28
accuracy			0.91	270
macro avg	0.89	0.88	0.88	270
weighted avg	0.91	0.91	0.91	270

A confusion matrix was generated to visualize class-wise prediction performance and identify potential misclassification patterns among closely related date varieties. The Fig.3 demonstrates that the proposed multiclass logistic regression-based date fruit grading framework achieves strong class-wise prediction performance across all seven date varieties. The pronounced diagonal dominance indicates a high rate of correct classification, confirming that the extracted features provide effective linear separability among most classes. Varieties such as DOKOL and SAFAVI exhibit near-perfect recognition, reflecting their distinct visual characteristics, while minor misclassifications are primarily observed between visually similar classes such as DEGLET and SOGAY, as well as BERHI and IRAQI. These limited errors suggest overlapping morphological attributes rather than model instability. The results indicate that logistic regression offers a reliable and interpretable classification mechanism for automated date fruit grading, with misclassification patterns providing valuable insight into varietal similarities and potential directions for feature enhancement.

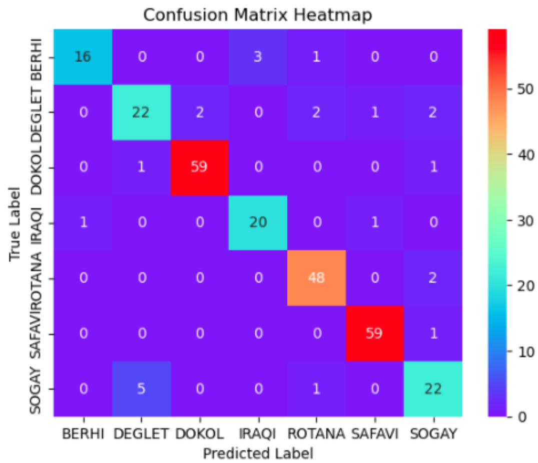

Figure 3. Confusion matrix of the proposed multiclass logistic regression based date fruit grading framework

A comparative evaluation (Table. 3) with other widely used classifiers further highlights the effectiveness of the proposed logistic regression–based date fruit grading framework. As shown in the performance comparison, logistic regression achieves the highest classification accuracy of 0.9111 while also reporting the lowest mean squared error (MSE) of 1.10, indicating superior predictive consistency and reduced error variance.

Table 3. Comparative evaluation with other widely used classifiers

	Model	accuracy	mse
0	Logistic Regression	0.911111	1.10
5	SVM	0.888889	1.23
3	XGBoost	0.888889	1.25
4	KNeighbours	0.862963	1.85
2	Random Forest	0.625926	2.70
1	Decision Tree	0.755556	2.72
6	AdaBoost	0.411111	3.26

To validate the effectiveness of the proposed Logistic regression framework, its performance was compared with several widely used machine learning classifiers, including Support Vector Machine, Random Forest, Decision Tree, K-Nearest Neighbors, XGBoost, and AdaBoost. All models were trained and evaluated under identical pre-processing and data-splitting conditions to ensure a fair comparison. The comparative analysis highlights the superiority of Logistic Regression in terms of classification accuracy and error minimization, while also demonstrating its computational efficiency and interpretability.

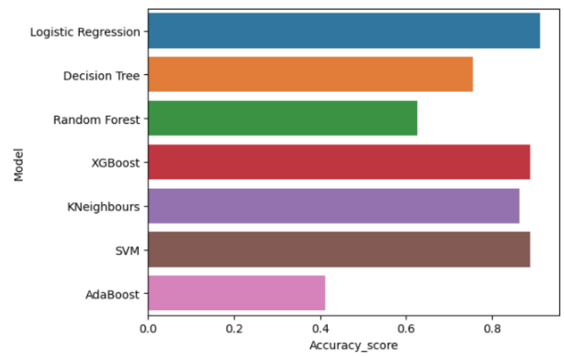

Figure 4 . Comparative evaluation of classification accuracy

A comparative evaluation of classification accuracy shown in Fig. 4, reveals that the logistic regression model achieves the highest performance among all the evaluated classifiers, attaining an accuracy of approximately 0.91. This result indicates its strong ability to discriminate among multiple date fruit varieties using the extracted features.

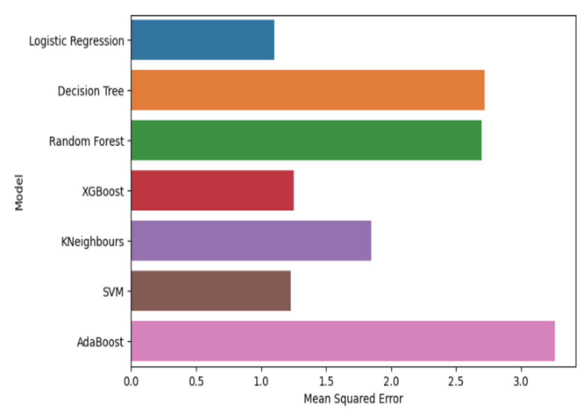

Figure 5. comparative evaluation of the mean squared error (MSE)

A comparative evaluation of the mean squared error (MSE) indicated in fig. 5, showing clear performance differences among the evaluated classifiers. The logistic regression model records the lowest MSE of 1.10, demonstrating superior predictive stability and minimal deviation between predicted and actual class outcomes.

VI. CONCLUSION

This paper presented an automated Date Fruit Grading Framework based on a Logistic Regression classifier for multi-class classification of seven commercially important date fruit varieties. The proposed approach was systematically evaluated using standard performance metrics and compared with several widely adopted machine learning algorithms to assess its effectiveness and reliability. Experimental results demonstrate that Logistic Regression achieved an overall classification accuracy of 91.11% with a mean squared error of 1.10, outperforming Support Vector Machine, XGBoost, K-Nearest Neighbors, Random Forest, Decision Tree, and AdaBoost classifiers under identical experimental conditions A detailed class-wise analysis revealed strong predictive performance across most date varieties, with high precision, recall, and F1-score values, particularly for DOKOL and SAFAVI classes, which exhibited F1-scores close to unity. The weighted average precision, recall, and F1-score values of 0.91 further confirm the robustness of the proposed framework, indicating balanced classification performance even in the presence of moderate class imbalance. The confusion matrix analysis showed minimal misclassification among visually similar date varieties, highlighting the discriminative capability of the Logistic Regression model when applied to appropriately prepared feature representations.

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