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Research Article

Comparative Evaluation of Machine Learning Algorithms for Raisin Variety Classification Based on Morphological Features

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ABSTRACT

Machine learning algorithms enable the rapid, accurate, and automated classification of agricultural products. Compared to human visual assessment, these algorithms provide more consistent and highly accurate determination of product characteristics such as variety and quality. In this study, machine learning algorithms were employed to classify Keçimen and Besni raisin varieties cultivated in Turkey. The Raisin dataset obtained from the UCI Machine Learning Repository was used as the data source. For the classification task, k-Nearest Neighbors (k-NN), Multilayer Perceptron (MLP), and Support Vector Machines (SVM) algorithms were utilized. The classification process was carried out using the WEKA software. Initially, the dataset was divided into 80% training and 20% testing subsets, and classification was performed accordingly. Subsequently, the classification process was repeated using the 10-fold cross-validation method. The obtained performance results were evaluated comparatively among the applied algorithms. The MLP algorithm achieved the highest performance, with an accuracy of 92.78% and an AUC of 0.968 under the 80% training–20% testing scheme. Under 10-fold cross-validation, MLP also produced the highest accuracy and AUC values of 87.22% and 0.928, respectively. Although the k-NN and SVM algorithms also produced satisfactory results, they did not reach the performance level of MLP. The findings demonstrate that the evaluated machine learning algorithms can provide effective classification performance for the two raisin varieties under the experimental conditions considered in this study.

1. INTRODUCTION

The agricultural sector holds significant economic and social importance. Quality control and classification of agricultural products are critical for increasing their market value and meeting consumer demands. Traditional classification methods, which are time-consuming and prone to errors, are increasingly being replaced by automated systems in modern agriculture. Machine learning and deep learning techniques have revolutionized this field by providing high accuracy and efficiency in the classification of agricultural products [1]. In particular, when combined with image processing techniques, these methods enable rapid and reliable classification based on the physical characteristics of products [2].

Machine learning algorithms such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) are widely used for the classification of agricultural products. For instance, Sonmez et al. achieved 99.84% success in wheat classification with SVM [3]. Bulduk and Sabanci proposed a hybrid model based on Swin Transformer and EfficientNetV2 for the classification of three corn varieties; the single model achieved 99.37% accuracy on 1050 images, while the hybrid model achieved 100% accuracy, demonstrating high performance [4]. In another study, Bulduk and Sabanci compared different SVM kernel functions for date classification; when using 13 features selected with MRMR, the accuracy increased from 91.79% to 92.07% [5]. The results show that feature selection is important in improving classification

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performance. The success of these methods in the agricultural sector has not only improved product quality but also reduced dependency on manual labor.

Raisins are a rich source of carbohydrates and a nutritious snack containing antioxidants, potassium, fiber, and iron [6]. Türkiye is one of the world's leading grape- and raisin-producing countries; approximately 30% of raisin varieties are consumed as table raisin varieties, 37% are processed as dried products, 3% are used in wine production, and the remaining 30% are used for other purposes [7]. In recent years, numerous studies have been conducted using machine learning and deep learning techniques for raisin varieties and raisin classification, demonstrating an increasing interest in automated classification approaches. Çınar et al. [8] focused on the automated classification of Keçimen and Besni raisin varieties using machine vision and artificial intelligence techniques. By evaluating morphological features through Logistic Regression, Multilayer Perceptron, and Support Vector Machines (SVM), the researchers determined that the SVM model provided the highest classification performance with an accuracy of 86.44%. Khojastehnazhand and Ramezani [9] developed a machine vision system to classify the quality of bulk raisin samples using texture-based features. Their study demonstrated that combining Gray-Level Run Length Matrix (GLRLM) features with a Support Vector Machine (SVM) algorithm achieved an accuracy of 85.55% in a 6-class scenario, although the performance decreased as the classification structure became more complex. Wang et al. [10] introduced a non-invasive classification method for raisins by integrating a total of 74 hybrid features encompassing morphological, color, and texture data extracted from RGB images. Their experimental results demonstrated that the combination of all feature types yielded the highest performance, with the Linear Discriminant Analysis (LDA) model achieving a 99% accuracy rate, significantly surpassing models based on individual feature sets. Yu et al. [11] developed a hybrid classification framework for raisin quality assessment by integrating color and texture features extracted from RGB and HSI color spaces. Utilizing the Least Squares Support Vector Machine (LSSVM) algorithm, the study achieved a 95% accuracy rate across four quality classes, highlighting that the fusion of color histograms and GLCM-based texture data significantly improves model reliability over individual feature sets. Bisri and Man [12] investigated the impact of sampling techniques, specifically stratified and shuffled sampling, on the performance of machine learning models for raisin classification. Their findings revealed that shuffled sampling outperformed stratified sampling with a top accuracy of 88.11%, demonstrating that the choice of sampling strategy is a critical factor in enhancing the reliability and performance of algorithms like Random Forest. Şahin [13] proposed an efficient classification approach for raisin grains by leveraging feature selection techniques to enhance model performance while reducing complexity. By identifying the most significant morphological feature through Random Forest-based importance analysis and utilizing it within a Multi-Layer Perceptron (MLP) model, the study achieved a superior accuracy rate of 94.07%. These findings suggest that focusing on a limited set of highly effective variables can lead to more accurate and streamlined classification compared to using all available morphological data. Ünal et al. [14] conducted a comparative analysis of Decision Trees and Random Forest algorithms for the binary classification of raisin varieties using a seven-feature dataset. Their experimental results indicated that the Random Forest model achieved a slightly superior and more stable performance with an accuracy of 85.44%, compared to 85.22% for the Decision Tree model, highlighting the effectiveness of classical machine learning methods for datasets with a limited number of features. Guo et al. [15] proposed a non-destructive method for classifying raisin varieties by combining Near-Infrared (NIR) spectroscopy with pattern recognition algorithms such as SVM, MCNN, and an improved AlexNet. Their experimental results showed that the SVM model, integrated with Principal Component Analysis (PCA), achieved a perfect classification accuracy of 100%, indicating that NIR spectroscopy is a highly effective and reliable approach for the rapid identification of raisin cultivars. Zhou [16] evaluated the performance of XGBoost, SVM, MLP, and Logistic Regression algorithms for classifying raisin varieties, identifying the "Extent" feature as the most critical variable in the process. The experimental results indicated that the SVM model outperformed the other classifiers, achieving a 91% accuracy rate and an AUC of 0.91, which underscores the efficacy of classical machine learning in automated agricultural grading. Dirik [17] introduced a hybrid classification approach by integrating Particle Swarm Optimization (PSO) with Artificial Neural Networks (ANN) to enhance the grading accuracy of raisin grains. While traditional models such as KNN and Random Tree achieved lower performance, the proposed PSO-ANN hybrid reached a perfect accuracy rate of 100%, demonstrating the significant impact of metaheuristic optimization on neural network efficiency in agricultural sorting tasks. Ramdhani et al. [18] investigated the impact of Genetic Algorithm (GA) based feature selection on the classification performance of Support Vector Machines (SVM) using the raisin dataset. Their experimental results demonstrated that the GA-optimized SVM model achieved a superior accuracy of 87.67% and an AUC of 0.930, outperforming other traditional algorithms such as Naive Bayes and Decision Trees by effectively refining the feature set. Dewi et al. [19] conducted a comparative analysis of Decision Tree and Support Vector Machine

(SVM) algorithms to classify Keçimen and Besni raisin seeds. By utilizing a multi-metric evaluation approach—including sensitivity, specificity, and Kappa coefficient—the researchers determined that the SVM model offered a more stable and reliable performance, outperforming the Decision Tree in accurately identifying raisin cultivars. Karimi et al. [20] developed an intelligent expert system to automate the purity and quality measurement of Golden Bleached raisins using texture-based image analysis. By extracting 146 features and applying Principal Component Analysis (PCA) for dimensionality reduction, the researchers found that the SVM classifier outperformed the ANN model with an accuracy of 92.71%, demonstrating its reliability for high-precision food quality monitoring. Yılmaz et al. [21] proposed a hybrid classification framework that integrates Convolutional Neural Network (CNN) based feature extraction with traditional machine learning algorithms such as KNN, XGBoost, and SVC. Their experimental findings indicated that these hybrid models significantly outperformed standalone classical methods, demonstrating that deep learning-based representation learning enhances both accuracy and stability in raisin cultivar classification. Kılıçarslan [22] introduced a hybrid classification framework for raisin grains by integrating Rotation Forest (ROF) with Stacked Autoencoder (SAE) algorithms to enhance automated grading efficiency. By leveraging the feature learning capabilities of deep learning alongside classical machine learning ensembles, the proposed decision support system achieved an accuracy of 91.50%, demonstrating superior performance and stability compared to standalone traditional or deep learning models. Raihen and Akter [23] conducted a comprehensive comparative study of various machine learning and deep learning architectures to classify raisin cultivars based on morphological features. Their findings highlighted that gradient boosting methods, specifically LightGBM, achieved a superior accuracy rate of 98.40% with high ROC-AUC scores, suggesting that boosting-based algorithms and deep neural networks provide a highly effective framework for automated agricultural grading. Mohamed and Abdulkader [24] introduced a high-performance deep learning model designed to overcome the limitations of existing raisin classification methods. By employing a rigorous preprocessing pipeline that included normalization and Principal Component Analysis (PCA) alongside optimized regularization techniques, the researchers achieved accuracy and F-score exceeding 91%, representing a 5% performance improvement over previously reported models in the literature.

In this study, the classification performances of k-Nearest Neighbors (k-NN), Multilayer Perceptron (MLP), and Support Vector Machines (SVM) were comparatively evaluated for distinguishing between Keçimen and Besni raisin varieties. The publicly available Raisin dataset obtained from the UCI Machine Learning Repository was used, and all experiments were conducted using WEKA software. The models were evaluated under both an 80% training–20% testing scheme and 10-fold cross-validation.

Although the dataset and machine learning algorithms employed in this study have previously been investigated in literature, the contribution of the present work lies in the systematic evaluation of k-NN, MLP, and SVM models under a unified experimental framework. Rather than proposing a new classification algorithm, the study comparatively examines algorithm-specific parameter configurations, including different neighborhood sizes for k-NN, hidden-layer neuron numbers for MLP, and kernel functions for SVM. All models were evaluated under the same experimental conditions using both an 80% training–20% testing split and 10-fold cross-validation. Their performances were assessed using accuracy, precision, recall, F1-score, Matthews correlation coefficient, confusion matrices, ROC curves, and AUC values. This consistent evaluation framework enables the relative strengths of the classifiers to be compared and provides information regarding their stability, generalization capability, and sensitivity to different validation strategies.

2. MATERIAL AND METHODS

2.1. Dataset

In this study, the Raisin Dataset was obtained from the UCI Machine Learning Repository and consists of 900 samples belonging to Keçimen and Besni raisin varieties cultivated in Turkey [25]. Each sample is represented by seven features extracted using image processing techniques:

Area: The number of pixels within the boundaries of the raisin.

MajorAxisLength: The length of the major axis.

MinorAxisLength: The length of the minor axis.

Eccentricity: The eccentricity value.

ConvexArea: The convex area.

Extent: The extent value.

Perimeter: The perimeter distance.

The dataset contains 450 samples from each class (Keçimen and Besni), thus exhibiting a balanced structure. A statistical summary of the features is presented in Table 1. The dataset was converted into the .arff format for use in the WEKA software.

Table 1. Descriptive Statistics of the Features

Feature	Mean	Standard Deviation	Min	Max
Area	87804.78	39008.42	25387	235047
Major Axis Length	430.94	116.75	225.63	941.54
Minor Axis Length	254.18	52.58	129.58	492.64
Eccentricity	0.83	0.09	0.45	0.97
Convex Area	91186.98	40797.45	26139	278217
Extent	0.70	0.05	0.45	0.84
Perimeter	1185	312.68	619	2697

2.2. Data Preprocessing

The dataset was converted into ARFF format and imported into WEKA for the classification experiments. No external normalization, standardization, feature transformation, or outlier removal filter was applied before model training. All seven original morphological features and all 900 observations were retained in order to evaluate the classifiers using the original feature representation and sample composition of the publicly available dataset. No explicit statistical outlier detection or removal procedure was applied. No observations were excluded solely because of extreme numerical feature values, since these values may represent the natural morphological variability of Keçimen and Besni raisin grains.

2.3. WEKA Software

WEKA (Waikato Environment for Knowledge Analysis) is an open-source software developed for implementing machine learning algorithms and performing data analysis [26]. It provides various functionalities such as data preprocessing, classification, clustering and visualization. In this study, the dataset was processed and the algorithms were evaluated using WEKA version 3.8.5.

2.4. Machine Learning Algorithms

The k-Nearest Neighbors (k-NN) algorithm is a simple yet effective learning method used for classification and regression problems in machine learning. It classifies a data point based on the labels of its k nearest neighbors and makes decisions using approaches such as majority voting or weighted averaging. The algorithm performs well particularly on small datasets and low-dimensional feature spaces; however, its computational cost may become high for large datasets [27]. The Multilayer Perceptron (MLP) is a machine learning algorithm based on artificial neural networks and is commonly used for both classification and regression tasks. MLP is a feedforward neural network consisting of an input layer, one or more hidden layers, and an output layer. Learning is achieved through the optimization of weights using the backpropagation algorithm [28]. The Support Vector Machine (SVM) is a powerful machine learning algorithm used for classification and regression problems. SVM aims to find the optimal hyperplane that separates data points, maximizing the margin between different classes [29]. This study aims to comparatively evaluate the effectiveness of the selected machine learning algorithms. The block diagram of the study is presented in Figure 1. The performance of the algorithms was evaluated using the 80% training–20% testing (Percentage Split) method and 10-fold cross-validation. Performance metrics including Accuracy, Precision, Recall, F1-score, and Matthews Correlation Coefficient (MCC) were used for evaluation.

Receiver Operating Characteristic (ROC) curves and Area Under the ROC Curve (AUC) values were additionally used to evaluate the discrimination capability of the classifiers. The ROC curves were generated using the prediction scores produced by the best-performing k-NN, MLP, and SVM configurations in WEKA. The Keçimen variety was defined as the positive class in all ROC analyses. AUC values closer to 1 indicate stronger discrimination between the Keçimen and Besni varieties, whereas a value of 0.5 indicates discrimination performance comparable to random classification.

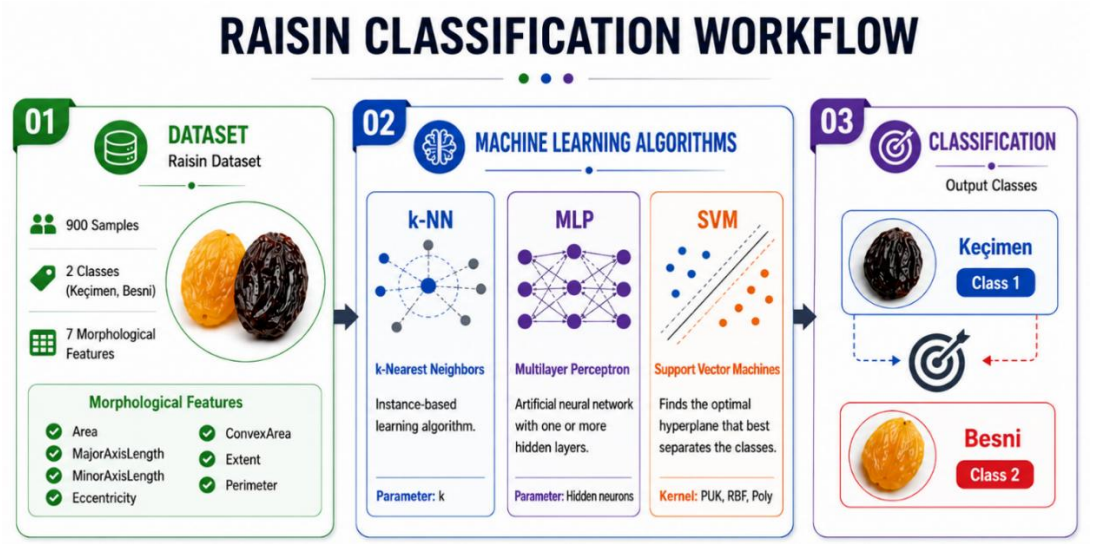


Figure 1. Workflow of the Study

3. RESULTS

3.1. Results Obtained with the k-NN Algorithm

In this study, classification was performed using different neighbor values in the k-NN algorithm, and the obtained results are presented in Table 2. According to the 80% training–20% testing split, the classification performance of the model improved as the value of k increased. The highest classification accuracy of 90% was achieved when the number of nearest neighbors was set to k = 7.

As shown in the confusion matrix in Figure 2, 81 samples were correctly classified and 10 samples were misclassified in the Keçimen class. Similarly, in the Besni class, 81 samples were correctly classified, while 8 samples were incorrectly predicted. These results indicate that the k-NN algorithm provides a relatively balanced classification performance for both classes. However, a limited number of misclassifications are still observed, suggesting that there is a certain degree of overlap between the feature distributions of the Keçimen and Besni classes. Furthermore, it is observed from Table 2 that increasing the k value initially improves the model performance, while further increases may lead to slight performance degradation. This behavior can be attributed to the trade-off between overfitting and underfitting, where smaller k values tend to overfit the data, and larger k values may oversmooth the decision boundaries.

Table 2. Results of k-NN Algorithm (80% Training-20% Testing)

k	Accuracy (%)	Precision	Recall	F1-Score	MCC
1	82.78	0.828	0.828	0.828	0.656
3	86.11	0.861	0.861	0.861	0.722
5	87.78	0.878	0.878	0.878	0.756
7	90.00	0.900	0.900	0.900	0.800
9	89.44	0.895	0.894	0.894	0.789

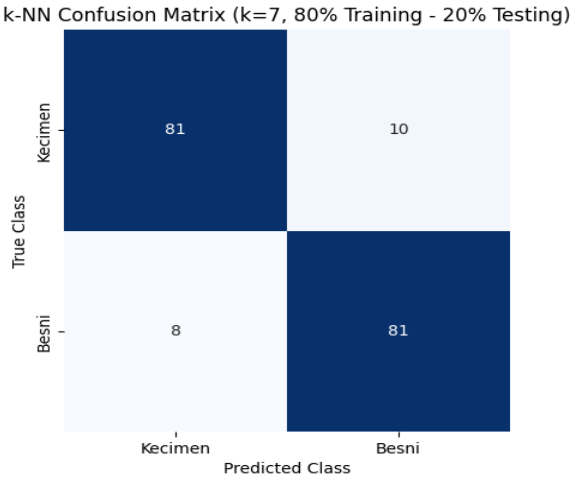


Figure 2. Confusion Matrix Obtained with k-NN Algorithm (k=7, 80% Training, 20% Test)

In this study, the performance of the k-NN algorithm was also evaluated using the 10-fold cross-validation method, and the obtained results are presented in Table 3. As can be observed, the classification performance generally improved with increasing values of k. The highest classification accuracy of 85.67% was achieved when the number of nearest neighbors was set to k = 9. As illustrated in the confusion matrix in Figure 3, 405 samples from the Keçimen class were correctly classified, while 45 samples were misclassified. Similarly, for the Besni class, 366 samples were correctly classified, whereas 84 samples were incorrectly predicted.

These results indicate that the k-NN algorithm provides a relatively consistent classification performance under the cross-validation scheme. However, compared to the hold-out validation approach, a slight decrease in overall accuracy is observed, which can be attributed to the more robust and unbiased evaluation mechanism of cross-validation.

Table 3. Results of k-NN Algorithm (10-fold Cross-Validation)

k	Accuracy (%)	Precision	Recall	F1-Score	MCC
1	81.44	0.814	0.814	0.814	0.629
3	82.55	0.827	0.826	0.825	0.652
5	84.22	0.844	0.842	0.842	0.686
7	85.11	0.853	0.851	0.851	0.704
9	85.67	0.859	0.857	0.856	0.716

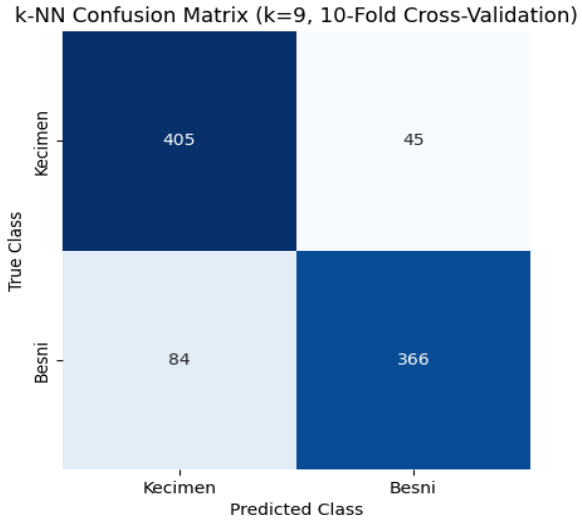


Figure 3. Confusion Matrix Obtained with k-NN Algorithm (k=9, 10-fold Cross-Validation)

3.2. Results Obtained with the MLP Algorithm

In this study, the classification performance of the Multilayer Perceptron (MLP) algorithm was evaluated using different numbers of neurons in the hidden layer. The results obtained are presented in Table 4. According to the 80% training–20% testing split, the highest classification accuracy of 92.78% was achieved when the number of neurons in the hidden layer was set to 7. As illustrated in the confusion matrix in Figure 4, 89 samples from the Keçimen class were correctly classified, while only 2 samples were misclassified. Similarly, in the Besni class, 78 samples were correctly classified, whereas 11 samples were incorrectly predicted.

These results indicate that the MLP algorithm demonstrates a high classification performance with very low misclassification rates, particularly for the Keçimen class. Compared to the k-NN algorithm, the MLP model provides improved classification accuracy and better generalization capability.

Overall, the experimental findings reveal that the MLP algorithm outperforms the k-NN approach under the hold-out validation scheme and provides a more robust and reliable classification performance on the Raisin dataset.

Table 4. MLP Algorithm Results (80% Training, 20% Testing)

number of neurons	Accuracy (%)	Precision	Recall	F1-Score	MCC
4	90.55	0.910	0.906	0.905	0.815
5	91.11	0.916	0.911	0.911	0.827
6	90.55	0.917	0.906	0.905	0.822
7	92.78	0.932	0.928	0.928	0.860
8	92.22	0.926	0.922	0.922	0.848
9	91.67	0.921	0.917	0.916	0.837
10	92.22	0.926	0.922	0.922	0.848

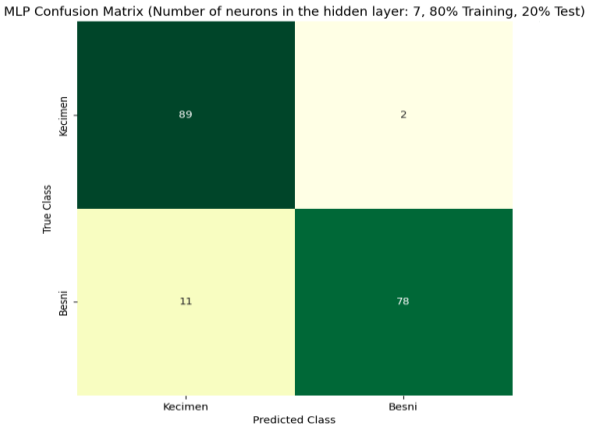


Figure 4. Confusion Matrix Obtained with MLP Algorithm (seven neurons in the hidden layer, 80% Training, 20% Test)

In this study, the performance of the Multilayer Perceptron (MLP) algorithm was also evaluated using the 10-fold cross-validation method. The results obtained for different numbers of neurons in the hidden layer are presented in Table 5. According to the results, the highest classification accuracy of 87.22% was achieved when the number of neurons in the hidden layer was set to 8. As illustrated in the confusion matrix in Figure 5, 406 samples from the Keçimen class were correctly classified, while 44 samples were misclassified. Similarly, in the Besni class, 379 samples were correctly classified, whereas 71 samples were incorrectly predicted.

These results indicate that the MLP algorithm provides a stable and reliable classification performance under the 10-fold cross-validation scheme. Although increasing the number of neurons generally improves the model performance up to a certain point, the slight decrease observed after 8 neurons suggests that further increasing the model complexity does not necessarily improve classification success.

Table 5. MLP Algorithm Results (10-fold Cross-Validation)

number of neurons	Accuracy (%)	Precision	Recall	F1-Score	MCC
4	86.33	0.864	0.863	0.863	0.728
5	86.44	0.865	0.864	0.864	0.730
6	86.89	0.870	0.869	0.869	0.739
7	86.89	0.871	0.869	0.869	0.740
8	87.22	0.874	0.872	0.872	0.746
9	87.00	0.872	0.870	0.870	0.742
10	87.11	0.873	0.871	0.871	0.744

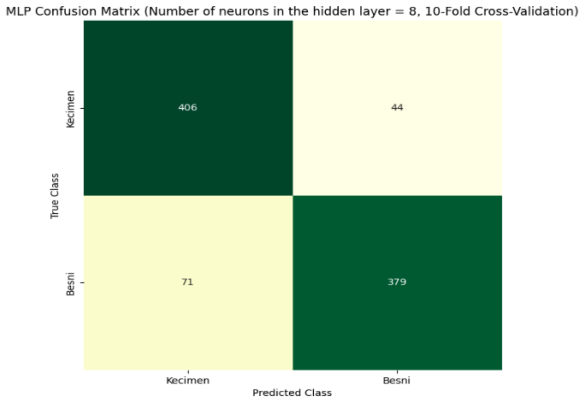


Figure 5. Confusion Matrix Obtained with MLP Algorithm (eight neurons in the hidden layer, 10-fold Cross-Validation)

3.3. Results Obtained with the SVM Algorithm

In this study, the classification performance of the Support Vector Machine (SVM) algorithm was evaluated using different kernel functions, including Poly Kernel, Normalized Poly Kernel, PUK, and RBF. The results obtained are presented in Table 6. According to the 80% training–20% testing split, the highest classification accuracy of 91.67% was achieved using the PUK kernel. As illustrated in the confusion matrix in Figure 6, 86 samples from the Keçimen class were correctly classified, while 5 samples were misclassified. Similarly, in the Besni class, 79 samples were correctly classified, whereas 10 samples were incorrectly predicted. These results indicate that the SVM algorithm, particularly with the PUK kernel, provides a strong and balanced classification performance across both classes. Compared to other kernel functions, the PUK kernel achieves higher precision, recall, F1-score, and MCC values, demonstrating its effectiveness in capturing the underlying data distribution. Furthermore, it is observed from Table 6 that while Poly and Normalized Poly kernels provide competitive results, their performance remains slightly lower than that of the PUK kernel. On the other hand, the RBF kernel shows a significantly lower classification accuracy, indicating that it is less suitable for this dataset.

Table 6. SVM Algorithm Results (80% Training, 20% Testing)

Kernel Function	Accuracy (%)	Precision	Recall	F1-Score	MCC
Poly Kernel	89.44	0.895	0.894	0.894	0.789
Normal Poly Kernel	89.44	0.895	0.894	0.894	0.789
PUK	91.67	0.918	0.917	0.917	0.835
RBF	79.44	0.854	0.794	0.785	0.644

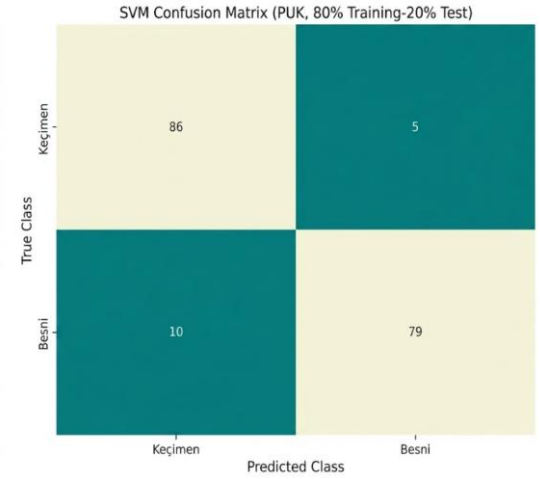


Figure 6. Confusion Matrix Obtained with SVM Algorithm (PUK, 80% Training-20% Test)

In this study, the performance of the Support Vector Machine (SVM) algorithm was further evaluated using the 10-fold cross-validation method with different kernel functions. The obtained results are presented in Table 7. According to the results, the highest classification accuracy of 86.67% was achieved using the PUK kernel. As illustrated in the confusion matrix in Figure 7, 412 samples from the Keçimen class were correctly classified, while 38 samples were misclassified. Similarly, in the Besni class, 368 samples were correctly classified, whereas 82 samples were incorrectly predicted.

These results indicate that the SVM algorithm with the PUK kernel maintains a stable and competitive classification performance under the cross-validation scheme. Although a slight decrease in accuracy is observed compared to the hold-out validation results, this is expected due to the more robust and unbiased nature of cross-validation. Furthermore, Table 7 shows that the Poly and Normalized Poly kernels produce similar performance levels, while the PUK kernel consistently achieves slightly better results across all evaluation metrics. In contrast, the RBF kernel yields the lowest performance, indicating that it is less suitable for the given dataset. Overall, the findings demonstrate that the SVM algorithm, particularly with the PUK kernel, provides reliable and consistent classification performance, achieving a good balance between model

complexity and generalization capability under the 10-fold cross-validation framework.

Table 7. SVM Algorithm Results (10-fold Cross-Validation)

Kernel Function	Accuracy (%)	Precision	Recall	F1-Score	MCC
Poly Kernel	86.44	0.866	0.864	0.864	0.731
Normal Poly Kernel	86.55	0.866	0.866	0.866	0.731
PUK	86.67	0.870	0.867	0.866	0.737
RBF	80.89	0.848	0.809	0.803	0.655

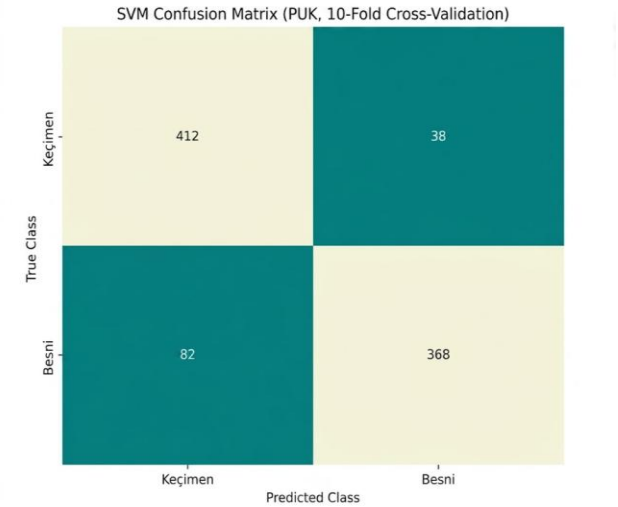


Figure 7. Confusion Matrix Obtained with SVM Algorithm (PUK, 10-fold Cross-Validation)

3.4. ROC Curve and AUC Analysis

ROC curve analysis was performed to provide a threshold-independent assessment of the discrimination capabilities of the best-performing k-NN, MLP and SVM configurations. The Keçimen variety was considered the positive class in all analyses. The AUC values obtained under the 80% training–20% testing scheme and 10-fold cross-validation are presented in Table 8.

Table 8. AUC Values of the Best-Performing Machine Learning Models

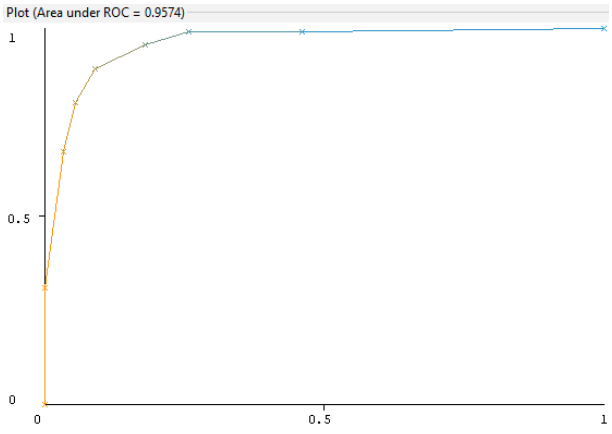
Evaluation strategy	Classifier	Best configuration	AUC
80% training–20% testing	k-NN	k = 7	0.957
80% training–20% testing	MLP	7 neurons in the hidden layer	0.968
80% training–20% testing	SVM	PUK kernel	0.962
10-fold cross-validation	k-NN	k = 9	0.912
10-fold cross-validation	MLP	8 neurons in the hidden layer	0.928
10-fold cross-validation	SVM	PUK kernel	0.914

Under the 80% training–20% testing scheme, the MLP model with seven neurons in the hidden layer achieved the highest AUC value of 0.968. The SVM model using the PUK kernel obtained a closely comparable AUC value of 0.962, while the k-NN model with k = 7 achieved an AUC of 0.957. These findings indicate that all three classifiers demonstrated strong discrimination capability between the Keçimen and Besni raisin varieties under the hold-out evaluation.

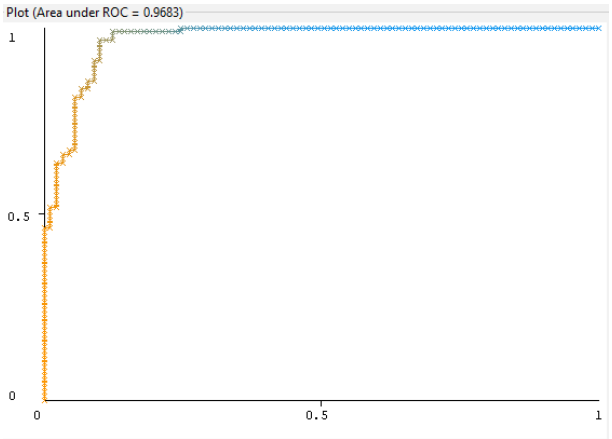
Under 10-fold cross-validation, the MLP model with eight neurons in the hidden layer again achieved the highest AUC value, reaching 0.928. The SVM model with the PUK kernel and the k-NN model with k = 9 yielded AUC values of 0.914 and 0.912, respectively. Although the AUC values were lower under cross-validation than under the fixed training–testing split, all three classifiers maintained effective discrimination performance. The decrease observed under cross-validation suggests that the fixed hold-out split may provide somewhat more optimistic performance estimates.

Figure 10 presents the classification success rates of the k-NN, MLP, and SVM algorithms obtained using the 80% training–20% testing approach. As shown in the figure, the MLP algorithm achieved the highest classification accuracy of 92.78%, outperforming both the k-NN and SVM models. The k-NN algorithm, with an optimal neighbor value of k = 7, achieved a classification accuracy of 90.00%, while the SVM algorithm using the PUK kernel reached an accuracy of 91.67%. Although all three models demonstrated high classification performance, the MLP model provided the most accurate results on the dataset. The results clearly indicate that the MLP algorithm is more effective in capturing the underlying patterns within the dataset, likely due to its ability to model complex nonlinear relationships. On the other hand, the SVM model also showed strong performance, closely following the MLP results, while the k-NN algorithm achieved slightly lower accuracy compared to the other methods. Overall, the comparative analysis demonstrates

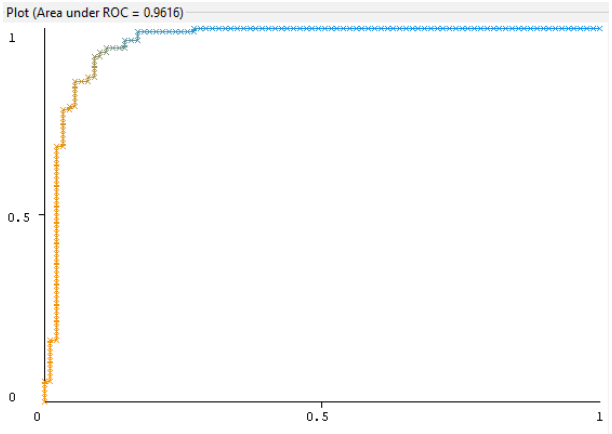
that while all models can produce reliable classification results, the MLP model offers the best performance under the hold-out validation scheme.



a.

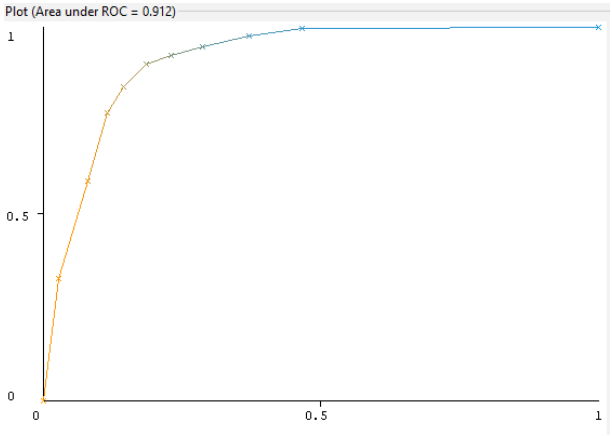


b.

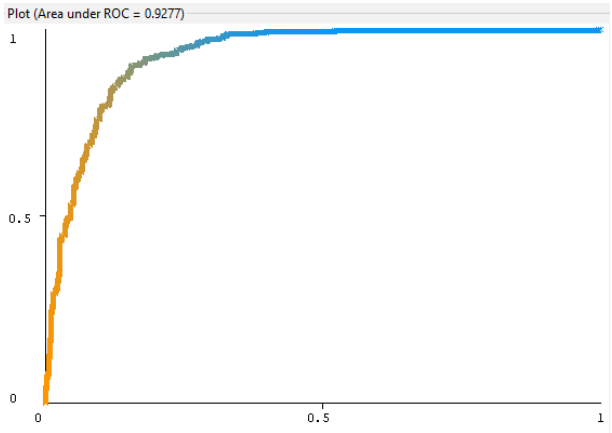


c.

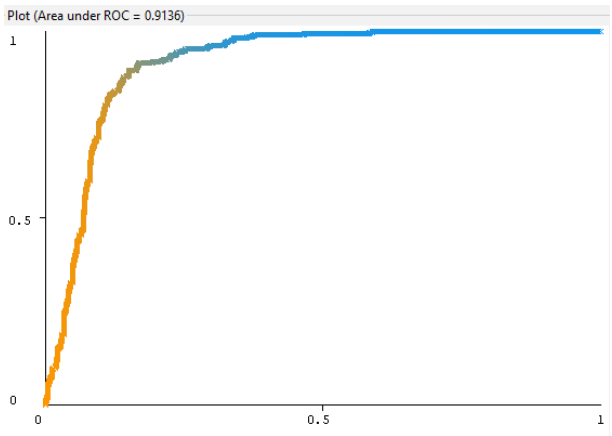
Figure 8. ROC Curves of the Best-Performing Models under the 80% Training–20% Testing Scheme: (a) k-NN, (b) MLP, (c) SVM



a.



b.



c.

Figure 9. ROC Curves of the Best-Performing Models under 10-Fold Cross-Validation: (a) k-NN, (b) MLP, (c) SVM

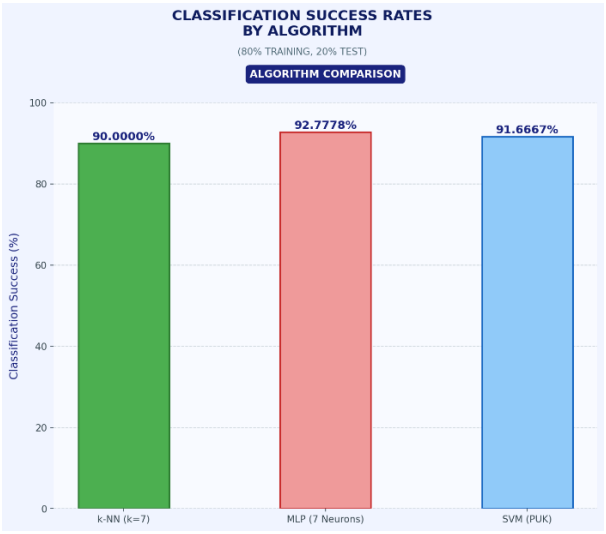


Figure 10. Classification Success Rates According to Machine Learning Algorithms (80% Training, 20% Testing)

3.5. Discussion

This study presents a comprehensive comparative analysis of three widely used machine learning algorithms—k-Nearest Neighbors (k-NN), Multilayer Perceptron (MLP), and Support Vector Machines (SVM)—for the classification of Keçimen and Besni raisin varieties based on morphological features. The experimental findings demonstrate that all evaluated models are capable of producing high classification performance; however, notable differences emerge depending on model architecture, parameter configuration, and evaluation methodology.

Accordingly, the contribution of the present study should primarily be interpreted as a controlled and consistent comparative benchmark rather than as the introduction of a novel classification algorithm. Evaluating different algorithm-specific configurations under identical experimental conditions makes it possible to examine not only the highest classification performance but also model stability, generalization capability, and sensitivity to the selected validation strategy.

Among the evaluated approaches, the MLP model achieved the highest classification accuracy of 92.78% under the 80% training–20% testing scheme when the number of hidden neurons was set to 7. This performance may be related to the ability of MLP models to represent nonlinear relationships among the input features. The observed results are consistent with existing literature, where neural network-based approaches are reported to outperform classical methods in datasets characterized by nonlinear feature interactions. Moreover, the relatively stable performance of MLP under cross-validation (87.22%) indicates a satisfactory generalization capability despite a moderate decrease compared to the hold-out evaluation.

The k-NN algorithm also demonstrated competitive performance, achieving its highest accuracy of 90.00% at $k = 7$ under the percentage split method. This suggests that distance-based learning can effectively capture the similarity structure of the dataset, particularly due to its balanced class distribution and low-dimensional feature space. However, the decrease in performance observed under 10-fold cross-validation (85.67%) indicates that k-NN is relatively sensitive to data partitioning and parameter selection. This behavior reflects the inherent limitation of instance-based learning methods, which rely heavily on local data distributions and may be affected by variations in training subsets.

For the SVM algorithm, the PUK kernel consistently yielded the best performance among the tested kernel functions, achieving 91.67% accuracy in the hold-out validation and 86.67% under cross-validation. These findings highlight the critical importance of kernel selection in SVM-based classification problems. While polynomial-based kernels provided competitive results, the significantly lower performance of the RBF kernel suggests that it may not be well-suited for the given feature distribution. Overall, SVM demonstrated a robust and balanced classification capability, closely following the performance of the MLP model.

Another important observation in this study is the consistent decrease in classification accuracy across all models when evaluated using 10-fold cross-validation compared to the percentage split method. The lower scores obtained under 10-fold cross-validation may reflect the models' sensitivity to data partitioning and the more conservative nature of evaluation across multiple folds. Therefore, cross-validation provides a more robust estimate of generalization performance than a single fixed split; however, the observed difference should not be interpreted as definitive evidence of overfitting. When compared to recent studies in the literature, the obtained results are slightly lower than those achieved by hybrid or deep learning-based approaches. This difference can be attributed to the limited number of handcrafted morphological features used in this study. Previous research has demonstrated that integrating color, texture, or deep feature representations significantly enhances classification performance. Therefore, the incorporation of feature engineering techniques or deep learning-based feature extraction methods could further improve the effectiveness of the models.

Overall, the findings confirm that classical machine learning algorithms remain effective and reliable tools for raisin classification tasks. However, achieving optimal performance depends heavily on appropriate model selection, parameter tuning, and the use of robust evaluation strategies.

The ROC–AUC findings were consistent with the accuracy, F1-score, and MCC results. The MLP classifier achieved the highest AUC under both evaluation strategies, with values of 0.968 for the hold-out evaluation

and 0.928 for 10-fold cross-validation. The SVM model obtained the second-highest AUC values, while k-NN produced slightly lower but still satisfactory results. The decreases in AUC from the hold-out evaluation to cross-validation were 0.045 for k-NN, 0.040 for MLP, and 0.048 for SVM. These findings reinforce the observation that model performance is affected by the selected validation strategy and that cross-validation provides a more conservative estimate of generalization performance.

To position the findings of the present study within the existing literature, Table 9 provides a comparative summary of previous studies on raisin variety and quality classification. The studies are compared in terms of the dataset used, feature representation, evaluated methods, and principal reported results. Since the reviewed studies differ in their datasets, class definitions, preprocessing procedures, feature extraction methods, and evaluation protocols, the reported performance values should be interpreted cautiously rather than regarded as directly equivalent results.

Table 9. Comparison of Previous Studies on Raisin Classification

Authors	Method Used	Main Results
Çınar et al. [8]	Logistic Regression, Multilayer Perceptron, and Support Vector Machine	SVM 86.44%
Zhou [16]	XGBoost, SVM, MLP, Logistic Regression	SVM 91%
Wang et al. [10]	Hybrid image-feature extraction and Linear Discriminant Analysis	LDA – 99%
Yu et al. [11]	Color histograms, GLCM texture features, and Least Squares Support Vector Machine	LSSVM – approximately 95%
Bisri and Man [12]	Stratified sampling, shuffled sampling, and machine-learning classifiers, including Random Forest	Shuffled sampling-based models – 88.11%
Ünal et al. [14]	Decision Tree and Random Forest	Random Forest – 85.44%
Ramdhani et al. [18]	Genetic Algorithm-based feature selection and SVM	GA-optimized SVM – 87.67%
Kılıçarslan [22]	Rotation Forest and Stacked Autoencoder	Stacked Autoencoder–Rotation Forest – 91.50%
Mohamed and Abdulkader [24]	Data normalization, PCA, regularization, and a proposed deep-learning model	Proposed deep-learning model – above 91%
In this study	**k-NN, MLP and SVM**	**MLP achieved the highest classification accuracy of 92.78%.**

As shown in Table 9, the reviewed studies address raisin classification using either the publicly available Raisin Dataset or other raisin image-, quality-, or spectroscopy-based datasets. The reported classification performances vary considerably depending on the dataset characteristics, class structure, feature representation, preprocessing procedure, model architecture, parameter optimization, data-splitting strategy, and validation protocol. Studies incorporating color, texture, spectral, or deep features generally reported higher performance than those relying solely on the original seven morphological attributes. Similarly, feature selection, ensemble learning, metaheuristic optimization, and hybrid architectures were associated with performance improvements in several studies. Therefore, the reported results should be interpreted cautiously and should not be regarded as directly equivalent because of differences in the datasets, input features, classification tasks, and experimental procedures.

In the present study, the MLP model achieved the highest hold-out accuracy and AUC values of 92.78% and 0.968, respectively. Under 10-fold cross-validation, the same algorithm remained the best-performing classifier, achieving an accuracy of 87.22% and an AUC of 0.928. Although some previous studies reported higher accuracy values, many of them employed additional color, texture, spectral, or learned features, together with feature-selection, optimization, ensemble, or hybrid modelling procedures. In contrast, the present study provides a controlled comparison of three established classifiers using the seven original morphological attributes, consistent evaluation criteria, and two different validation strategies. The difference between the hold-out and cross-validation results further demonstrates the influence of the validation protocol on the estimated classification performance.

One limitation of the present study is that no common dataset-level normalization or standardization procedure was externally applied to all classifiers before model training. Since the seven morphological attributes have substantially different numerical ranges, the absence of a unified scaling procedure may have influenced the performance of scale-sensitive algorithms. Therefore, the comparative results should be interpreted within the preprocessing and classifier settings used in this study. Future studies should systematically compare original, normalized, and standardized feature representations under the same validation protocol and should employ a separate validation set or nested cross-validation for parameter selection.

4. CONCLUSIONS

In this study, the classification performance of three fundamental machine learning algorithms—k-NN, MLP, and SVM—was systematically evaluated for distinguishing between Keçimen and Besni raisin varieties

using the Raisin dataset. The results clearly demonstrate that all three algorithms are capable of achieving high classification accuracy, confirming the effectiveness of machine learning techniques in agricultural product classification.

Among the evaluated models, the MLP algorithm achieved the best overall performance with an accuracy of 92.78% under the percentage split method, indicating its strong capability to model nonlinear relationships within the dataset. The ROC analysis further supported this result, as MLP achieved the highest AUC values of 0.968 under the hold-out evaluation and 0.928 under 10-fold cross-validation. The SVM model, particularly with the PUK kernel, also provided highly competitive results with an accuracy of 91.67%, while the k-NN algorithm achieved a maximum accuracy of 90.00% at k = 7. These findings indicate that although all models perform well, neural network-based approaches offer a slight advantage in terms of classification accuracy. The results obtained from 10-fold cross-validation revealed a consistent decrease in performance across all models, emphasizing the importance of robust and unbiased evaluation strategies. This highlights that relying solely on a single train-test split may lead to overly optimistic performance estimates.

The findings of this study suggest that classical machine learning algorithms can provide reliable, efficient, and interpretable solutions for raisin classification when appropriate parameter optimization and evaluation methodologies are applied. However, considering the increasing success of hybrid and deep learning-based approaches reported in the literature, there remains significant potential for further improvement.

For future research, it is recommended to explore larger and more diverse datasets, systematically compare original, normalized, and standardized feature representations, and incorporate advanced feature selection and feature engineering techniques. Deep learning-based architectures such as Convolutional Neural Networks or hybrid models may also be investigated. Additionally, integrating image-based color and texture features with morphological attributes may further improve classification accuracy and model robustness.

Declaration of Ethical Standards

The authors confirm that this study adheres to all ethical standards, including proper authorship attribution, accurate citation, appropriate data reporting and the publication of original research.

Credit Authorship Contribution Statement

The conceptualization of the research and the data collection process were carried out by Hüseyin Bulduk. The evaluation and analysis of the results were performed by Kadir Sabancı. The original draft of the manuscript was written by Hüseyin Bulduk, while the review and editing were undertaken by Kadir Sabancı.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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Availability of Data and Material

The dataset used in this study is publicly available from the UCI Machine Learning Repository.

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