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ORIGINAL ARTICLE

Apple (*Malus domestica*) Quality Evaluation Based on Analysis of Features Using Machine Learning Techniques

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Abstract
The use of artificial intelligence and machine learning algorithms for assessment of apple quality was evaluated in this study. Apples are renowned for containing a variety of nutritional elements. By analyzing apple characteristics, the study aimed to categorize apple quality, thus promoting apple consumption and production. The dataset used consists of 4000 data and eight features provided by an American agricultural company. There were two quality classes of apples: there were 2004 quality apples and 1996 low-quality apples. Artificial intelligence classification algorithms such as multilayer perceptron (MLP), support vector machine (SVM), random forest (RF), k-nearest neighbor (k-NN), and decision tree (DT) have were to predict apple quality. The performance of the algorithms was evaluated on their ability to accurately predict the quality level of the apples. According to the results of the study, the MLP algorithm achieved the highest classification success with an accuracy rate of 95.63%. The accuracy values of the other algorithms were SVM with 90.75%, k-NN with 89.75%, RF with 89.63%, and DT with 81%. Apple quality is not achieved by relying on a single feature, but rather by evaluating all the features affecting the apple together. An ideal level of acidity enriches the flavor and texture of food, whereas excessive acidity leads to a sour taste. Due to this complexity, we classified factors affecting apple quality and examined traits separately.

Keywords Apple quality · Classification of apples · Machine learning · Apple dataset · Quality classification

Introduction

Apple (*Malus domestica*) is a popular agricultural product with very high nutritional value. Apart from being a delicious fruit, it is also highly valuable for health due to its rich content of vitamins, minerals, fiber, and antioxidants. Apple variety varies according to criteria such as color, shape, taste, aroma, water content, and firmness. Accordingly, each apple has different quality. The quality of the fruit has a decisive impact on consumers' preferences and health. Food suppliers currently measure apple quality considering basic descriptors such as fruit shape, size, color, soluble solid content, and acidity level. Using the commonly used penetrometer method in the industry, fruit firmness is measured and its characteristics are determined. These specified methods result in significant workload, time loss, and extra costs. Particularly in recent years, there has been an increased interest in fruits with high quality and safety standards. As a result, the demand for automated, accurate, and fast quality identification, as well as the search for innovative solutions, continues to increase. At the same time, consumer

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demands for high-quality horticultural products are also becoming more diversified over time. At this point, artificial intelligence and machine learning techniques offer potential advantages in optimizing the process of determining apple quality (Harker et al. 1998; Hoehn et al. 2003; Li et al. 2021; Marigheto et al. 2008; Musacchi and Serra 2018).

Machine learning algorithms make the process of determining apple quality more effective by learning from large datasets. These techniques automate business processes, save time, and minimize human errors. Moreover, they help agricultural producers reduce costs by assisting in the rapid and accurate evaluation of apple quality. Artificial intelligence and machine learning reduce the workload caused by traditional methods, providing an automated and reliable quality control process. The ability to respond to consumer demands more quickly and accurately enables better alignment with market demands (Gencturk et al. 2023; Hassan et al. 2023; Karthikeyan et al. 2024; Sun et al. 2021). In this study, factors that are effective in determining the quality of apples were also examined. In this context, the aim was to develop prediction models for apple quality and provide concrete information to growers about fruit quality.

The characteristics of apples, such as juiciness, acidity level, size, weight, sweetness, crunchiness, and ripeness, are determined rapidly and accurately by artificial intelligence algorithms, enabling the analysis of apple characteristics. This analysis provides significant guidance to apple producers for producing more flavorful and higher quality products. Artificial intelligence models assist growers in identifying factors that enhance quality, particularly considering factors such as juiciness, crunchiness, and acidity balance in apples. This study enables the assessment of apples as "quality" or "low-quality" based on their characteristics. Apple growers can leverage this information to gain a competitive advantage in marketing their products during the sales process (Cetin et al. 2022; Deb et al. 2021; Karthikeyan et al. 2024; Musacchi and Serra 2018).

Related Works

As the literature lacks comprehensive coverage of factors affecting apple quality, researchers have also delved into studies on determining the quality of various fruits. These investigations reveal a trend of classifying fruits based on their images using image processing and machine learning algorithms. A summary of these insightful studies is presented here.

Suryanti and Rohman developed a citrus species classification system based on leaves. Using a total of 117 data, they designed a classification system to determine low-quality and high-quality apples, achieving an accuracy of 88.37% (Suryanti and Rohman 2024). In another study, Bird et al. conducted research on fruit quality classification. They created a model using 1056 lemon images in their dataset. The best model they obtained achieved an accuracy rate of 81.99% with a structure containing 4096 interpretation neurons. After applying data augmentation techniques, they increased the classification accuracy from 83.77% to 88.75% (Bird et al. 2022). Jahanbakhshi et al. aimed to use a developed convolutional neural network (CNN) algorithm to detect the quality of lemons and classify them. The dataset consisted of two classes: healthy lemons and unhealthy lemons. As a result, they achieved 100% accuracy using the CNN algorithm (Jahanbakhshi et al. 2020). In another study, Minh Trieu and Thinh used a CNN algorithm to detect the quality of dragon fruit based on its external appearance. They achieved an accuracy of 96% using the CNN algorithm (Minh Trieu and Thinh 2021). Pratondo and Novianty aimed to create a classifier using machine learning to identify pear images. In their study, they observed that a classifier created using Inception-v3 achieved the best performance with an accuracy rate of 94.00% (Pratondo and Novianty 2022).

The literature studies on apple quality and the external factors influencing apple quality are included in this section. Additionally, a summary of the studies conducted is presented in Table 1.

Gong et al. examined the physical and chemical properties of 30 apple varieties grown in the same region. Within the scope of the study, meticulous analysis was conducted on 20 quality parameters of apple samples (weight, volume, density, color, firmness, sugar–acid ratio, vitamin C, etc.). In terms of density, fruit shape index, and water content, there were no statistically significant differences among the 30 apple varieties. Principal component analysis was used

Table 1 Summary of apple research findings in the literature

No.	Dataset quantity	Class number	Method	Accuracy (%)	References
1	3000	3	Imp-ResNet50	96.50	(Sun et al. 2021)
2	3600	3	SVM	77.67	(Li et al. 2021)
			CNN	95.33	
3	3266	2	CNN GoogLeNet AlexNet	87.24 100 99.69	(Ibrahim et al. 2022)
4	80	2	k-NN	97.50	(Baneh et al. 2023)

to examine the remaining 17 measurements. Principal component analysis showed that the first six components explained 83.56% of the variance and represent a significant portion of the variability. The 30 apple varieties were classified into five main groups using hierarchical cluster analysis. Score plots from principal component analysis support this classification (Gong et al. 2014).

Sun et al. employed CNN to classify six different apple varieties. Segmented image data were processed using deep convolutional generative adversarial networks (DCGAN) for data augmentation purposes. Subsequently, an enhanced ResNet50 model, named "Imp-ResNet50," was proposed. The results indicate that the proposed method could generate high-quality training examples and effectively reduce the processing time. By combining SVM, DCGAN, and Imp-ResNet50, they achieved a classification accuracy of 96.5% (Sun et al. 2021).

According to Li et al., apple exports are affected by blemishes on apple skin. Using real images, they identified and classified apple quality. In their study, real images of 'Yantai Red Fuji' apples were used, which varied in time, angle, and light intensity. A mobile camera was used to capture 3600 original images. Researchers proposed a CNN-based model to grade apples rapidly and accurately. Tested on an independent dataset, the proposed model achieved 95.33% accuracy. Thus, the proposed model detects and classifies apple quality (Li et al. 2021).

An automatic fruit classification process was needed to meet the increasing demand for high-quality fruits in the market, according to Ibrahim et al. Training and testing were thus conducted on 3266 image samples. By analyzing apple images, the authors developed and evaluated three different CNN models to categorize fresh and rotten apples. The models included CNN, GoogLeNet, and AlexNet. With 100% accuracy, GoogLeNet outperformed AlexNet and traditional CNN. An evaluation of three CNN model architectures is presented in their study (Ibrahim et al. 2022).

Baneh et al. employed a combination of machine learning techniques for the detection of body and calyx in a low-cost apple sorting machine. Precise body/calyx shape extraction led to more accurate feature extraction and classification. They determined that the k-NN classifier with the highest accuracy rates used the 5-nearest neighbor classifier and Euclidean distance with 80 training examples. According to the results, this method produced the best accuracy rates of 100% for body and 97.5% for calyx (Baneh et al. 2023).

Table 1shows the results of studies on apple quality classified on the basis of apple images. In this study, classification was carried out by focusing on various characteristics

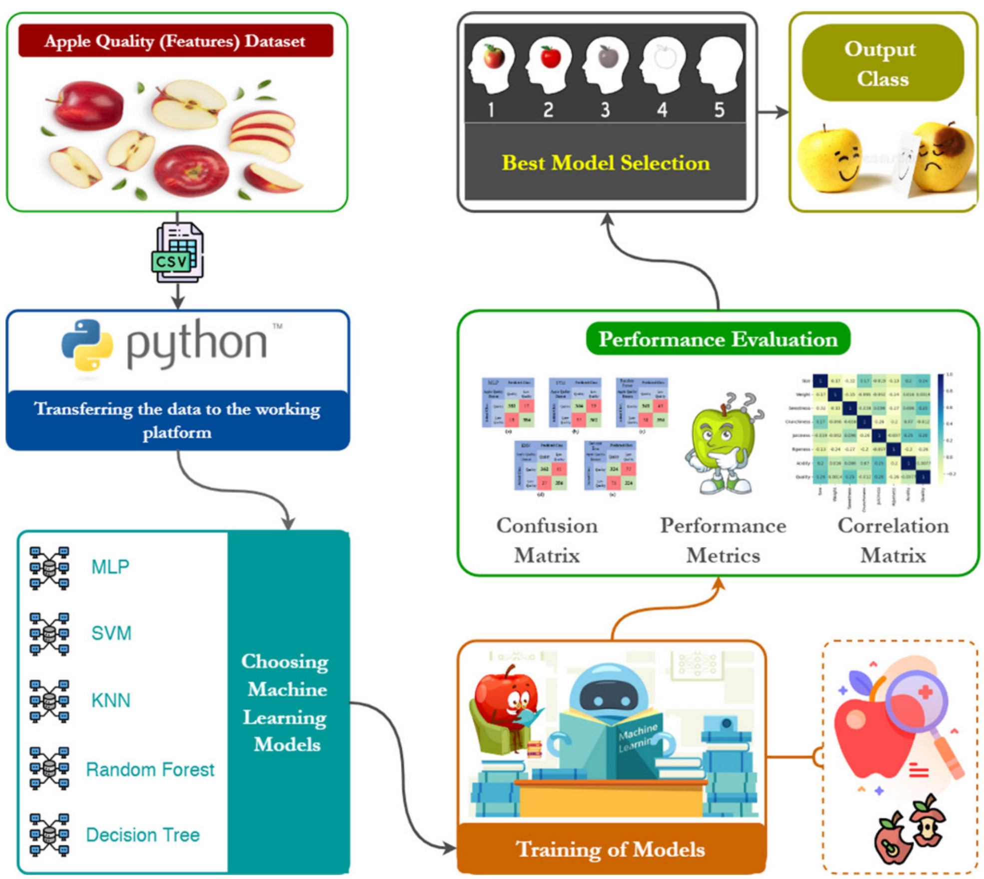

Fig. 1 Flow diagram illustrating the procedural workflow of the study

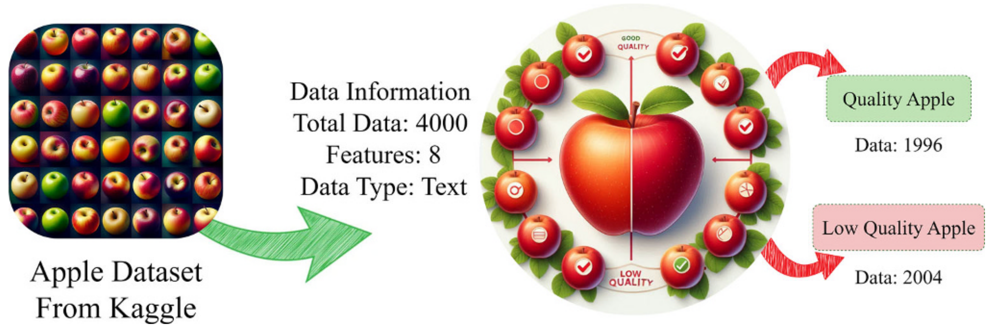

Fig. 2 Details regarding the apple dataset

of apples, which adopts a different approach from other studies. The most significant difference that sets this study apart from others is the comprehensive quality classification by evaluating various characteristics of apples together, rather than solely focusing on visual quality. This approach not only considers the external appearance of the apple but also focuses on various attributes such as maturity, acidity, juiciness, and sweetness, providing a more detailed assessment. Consequently, after determining apple quality comprehensively, the study investigated the combined effect of various factors on quality.

Materials and Method

Machine learning algorithms commonly preferred in the literature for determining apple quality were utilized. These algorithms include SVM, RF, k-NN, DT, and MLP. For classification processes, the Python programming language and the scikit-learn machine learning library were preferred. The flow diagram for this study is provided in Fig. 1and shows the overarching methodology of the study. The main objective of the study is to effectively address the process of determining apple quality and evaluate the performance of different machine learning algorithms.

Dataset Description

The dataset used in this study contains various attributes of apples, providing detailed information about the qualities of apples. The "Apple Quality" dataset from the Kaggle platform (Elgiriyewithana 2024) was used in the study. The dataset, obtained from an American agricultural company, consists of 4000 data for eight features. Features included the size, weight, sweetness level, crunchiness, juiciness level, ripeness stage, acidity level, and overall quality of each apple. Upon examining the distribution of quality classes in the dataset, it was found that there were 2004 high-quality apples and 1996 low-quality apples (Elgiriyewithana 2024). This study aimed to determine apple quality for use in quality classification processes. A visual presentation in Fig. 2 provides more information about the dataset.

The features of the dataset are detailed in Table 2. Information about various characteristics such as the size, weight, sweetness level, crunchiness, juiciness level, ripeness stage, acidity level, and overall quality of each fruit is provided. These attributes contain important data to understand the general characteristics of the fruits and their species-specific qualities.

Multilayer Perceptron

In complex datasets, MLP is one of the artificial neural networks used for pattern recognition, classification, and learning. An MLP consists of an input layer, one or more hidden layers, and an output layer. External data are received during input, while output is produced for a specific task. Layers are designed to extract learned features and model complex relationships. Activation functions are applied to incoming data by neurons in each hidden layer. The network learns complex relationships through this process. MLP is trained by using the backpropagation algorithm. In backpropagation, weights are updated to minimize errors between outputs and actual values. A specific task is repeated iteratively to make the network more efficient; MLP can handle nonlinearly separable datasets best (Hayta et al. 2023; Koklu and Sabanci 2015).

Table 2 Description of dataset features

Features	Description
Apple_ID	Unique identifier for each fruit
Size	Size of the fruit
Weight	Weight of the fruit
Sweetness	Degree of sweetness of the fruit
Crunchiness	Texture indicating the crunchiness of the fruit
Juiciness	Level of juiciness of the fruit
Ripeness	Stage of ripeness of the fruit
Acidity	Acidity level of the fruit
Quality	Overall quality of the fruit

Support Vector Machine

The primary goal of an SVM is to find a hyperplane that best separates two classes. This hyperplane divides the data points into two classes in a way that both classes are as homogeneous as possible and well-separated from each other. This hyperplane is the one that provides the largest margin between the data points, known as "the margin." Generally, while SVM is a powerful tool for binary classification problems, it is essential to perform proper parameter tuning and consider the size of the dataset (Abdullah and Abdulazeez 2021).

k-Nearest Neighbor

A supervised learning algorithm used to solve classification problems is k-NN. This algorithm plays an effective role in determining whether features belong to a specific class or not. Among the critical factors to consider in optimizing the algorithm are determining the number of neighbors and the distance measurement method. The selection of the number of neighbors plays a significant role in determining the algorithm's performance; using too many neighbors can increase complexity, while using too few neighbors can risk overfitting. The Euclidean distance, commonly used as the distance measurement method, is effective in evaluating similarity between features. The k-NN algorithm requires the determination of optimal parameters through trial-and-error methods and carefully designed experiments. The correct selection of these parameters ensures that the algorithm is used successfully and effectively (Koklu and Sabanci 2015; Taspinar et al. 2020; Wang et al. 2007). The method for calculating the Euclidean distance is provided in Eq. 1 (Koklu and Sabanci 2015; Yong et al. 2009).

$$d\left(x_i, x_j\right) = \left(\sum_{s=1}^{p} \left(x_{is} + x_{js}\right)^2\right)^2 \qquad (1)$$

In Eq. 1, *xi* and *xj* represent two different points and are used to calculate the distance between them. The summation ($\sum$) operation in the equation represents the sum of squares performed across each feature dimension between the points. The Euclidean distance formula is a fundamental measure used to calculate the distance between two points (Yong et al. 2009).

Random Forest

Random forests combine tree predictions based on a random vector with the same distribution, each independently sampled. Increasing the number of trees in a forest tends to reduce the generalization error. In a forest, the generalization error of tree classifiers depends on the strength of individual trees. Multiple decision trees are aggregated in RFs. In trees, observations are selected using a bootstrap random sampling method and variables are selected using a random subspace method. The remaining data are used to evaluate the performance of trees and determine variable importance after two-thirds of the dataset is used to build trees. By combining decision trees and sampling strategies, this model uses a general aggregation rule. Random forests are known for their effectiveness in high-dimensional datasets, image recognition, and classification (Breiman 2001; Rigatti 2017).

Decision Tree

Data classification representation uses decision trees (DTs). Classifiers based on DT algorithms learn and discover patterns in datasets. Using a series of decision rules, these algorithms can classify or predict a dataset. From a root node, a tree analyzes the dataset through nested decision nodes. Based on the result of each internal node, the algorithm directs the data point to the next node. As a result, the data point can be assigned to a class or predicted. As part of the learning process, DT classifiers split branches of the DT and assign class labels to each leaf node. In addition, these classifiers incorporate various methods for determining feature importance rankings and improving generalization (Charbuty and Abdulazeez 2021).

Confusion Matrix

Confusion matrix is an important metric used to evaluate the classification performance of a model. Typically used in classification problems, it compares the actual values of the model with the values it predicts.

The matrix contains four main components, representing whether the model correctly predicts a particular class (Gencturk et al. 2023; Koklu and Sabanci 2016; Visa et al. 2011). The confusion matrix for a binary classification problem is shown in Table 3.

The metrics provided in Table 3 allow for a detailed evaluation of the model's performance and are used in calculating various performance criteria. The descriptions of the metrics are as follows:

- TP (true positive): The number of apples correctly classified as high-quality that are indeed high-quality.
- FP (false positive): The number of apples incorrectly classified as high-quality when they are actually low-quality.
- TN (true negative): The number of apples correctly classified as low-quality that are indeed low-quality.

Table 3 Two-class confusion matrix

		Actual class	
		Positive (P)	Negative (N)
Predicted Class	True (True)	TP	TN
	False (False)	FP	FN

- FN (false negative): The number of apples incorrectly classified as low-quality when they are actually high-quality.

Correlation Matrix

The correlation matrix is a fundamental tool in statistical analysis, measuring the quantitative relationship between variables. It helps determine the strength and direction of the relationship between variables. Each variable is cross-referenced with all other variables in the correlation matrix (Zhuang et al. 2020).

Each cell in the correlation matrix represents the correlation coefficient between two variables. This correlation coefficient takes a value between –1 and 1:

- –1: Represents a perfect negative relationship. One variable decreases as the other increases.
- 0: There is no relationship between the two variables.
- 1: Represents a perfect positive relationship. One variable increases as the other increases.

Performance Metrics

Various performance metrics are used to evaluate classifier performance. In this study, metrics such as accuracy, F1-score, recall, and precision, calculated based on true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) values, are considered. These metrics are used to understand and assess the classification performance of the model. The details of the calculations are presented in Table 4 (Acharya et al. 2019).

The explanations of the performance metrics are (Satorres Martínez et al. 2018) as follows:

- *Accuracy:* It is a measure indicating how much of a model's predictions are correct.
- *Precision:* It is a measure indicating how many of the examples predicted as "positive" by a model are actually "positive."
- *Recall:* It is a measure indicating how many of all positive examples a model correctly predicts.
- *F1-Score:* It is a measure showing the balance between precision and recall.

Bivariate Analysis

Statistical analysis conducted to examine the relationship between two variables is a method used to understand the relationship between these variables and determine the nature of this relationship. This analysis aims to reveal the strength, linearity, or inverse proportionality of relationships in the dataset by evaluating dependencies, interactions, and correlations between variables. Thus, a deeper understanding of the relationship between variables is obtained, and whether this relationship is statistically significant is assessed (Stricker et al. 2023).

Multivariate Analysis

The purpose of multivariate analysis is to examine multiple variables together and understand their relationships. Analyzing datasets enables researchers to understand and explain complex structures. Furthermore, it is used to determine causal relationships between variables, evaluate relationships between variables, and predict future events. Analyzing datasets with this method reduces complexity and uncovers meaningful relationships (Moghaddam et al. 2022).

Experimental Results

In this section, the results of analyses of five different models created with machine learning algorithms are presented. Various machine learning algorithms were applied to 4000 data consisting of eight different features related to apple quality. These algorithms are MLP, SVM, RF, k-NN, and DT. The results are shown in Table 5.

Table 4 Performance metric formulations

Performance metrics	Formula	References
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	(2)
Precision	$\frac{TP}{TP+FP}$	(3)
Recall	$\frac{TP}{TP+FN}$	(4)
F1-Score	$\frac{2TP}{2TP+FP+FN}$	(5)

Table 5 Performance metrics of all models

	MLP (%)	SVM (%)	RF (%)	k-NN (%)	DT (%)
Accuracy	95.63	90.75	89.63	89.75	81
Precision	95.62	90.75	89.64	89.77	81
Recall	95.62	90.75	89.63	89.75	81
F1-Score	95.63	90.75	89.62	89.75	81

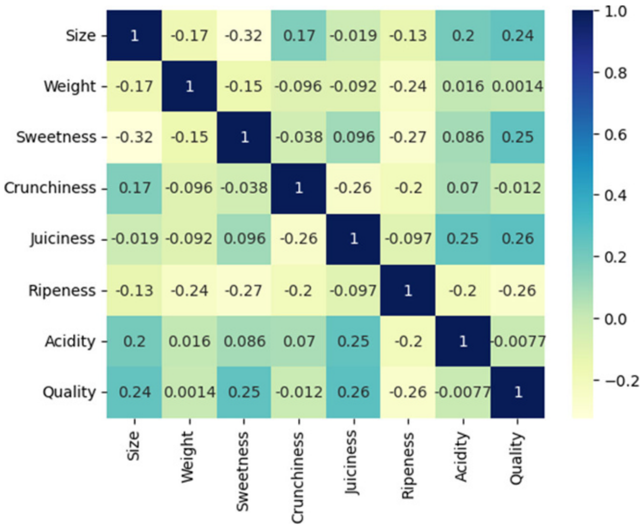

Fig. 3 Correlation matrix results

These results compare the performance of different machine learning algorithms in predicting apple quality. While the MLP algorithm provided the highest accuracy rate, the DT algorithm had the lowest performance.

Result of Correlation Matrix

It is possible to obtain information about the relationships between variables by looking at the correlation matrix in Fig. 3. In the correlation matrix, 1 indicates a positive relationship, 0 indicates no relationship, and –1 indicates a negative relationship. The closer the values are to 1, the stronger and more positive the relationship is observed to be; the closer they are to –1, the stronger and more negative the relationship is observed to be.

In the analysis of the correlation matrix in Fig. 3, a positive correlation (0.24) between size and quality is observed, but this relationship can be considered weak. There is almost no correlation between weight and quality (0.0014), indicating no relationship between the two variables. There is a positive correlation (0.25) between sweetness and quality, but this relationship can be considered weak. There is almost no correlation between crispiness and quality (–0.012), indicating no relationship between the two variables. There is almost no correlation between acidity and quality (–0.0077), indicating no relationship between the two variables. There is a negative correlation (–0.26) between ripeness and quality, but this relationship can be considered weak. There is a positive correlation (0.26) between juiciness and quality, but this relationship can be considered weak.

It can be seen that size with a correlation of 0.24, sweetness with 0.25, and juiciness with 0.26 are the three most important variables contributing to the apple being of high quality. It is observed that the variable with the most impact on the apple being of low quality is ripeness with –0.26.

Confusion Matrix Result

Following the training of the dataset, the confusion matrix results generated based on the learning performance of five different machine learning algorithms (MLP, SVM, RF, k-NN, DT) are presented in Fig. 4.

According to the confusion matrix of the MLP model shown in Fig. 4, it contains 381 true positives and 17 false

Fig. 4 Confusion matrix of all models: **a** multilayer perceptron (*MLP*), **b** support vector machine (*SVM*), **c** random forest (*RF*), **d** k-nearest neighbor (*k-NN*), **e** decision tree (*DT*)

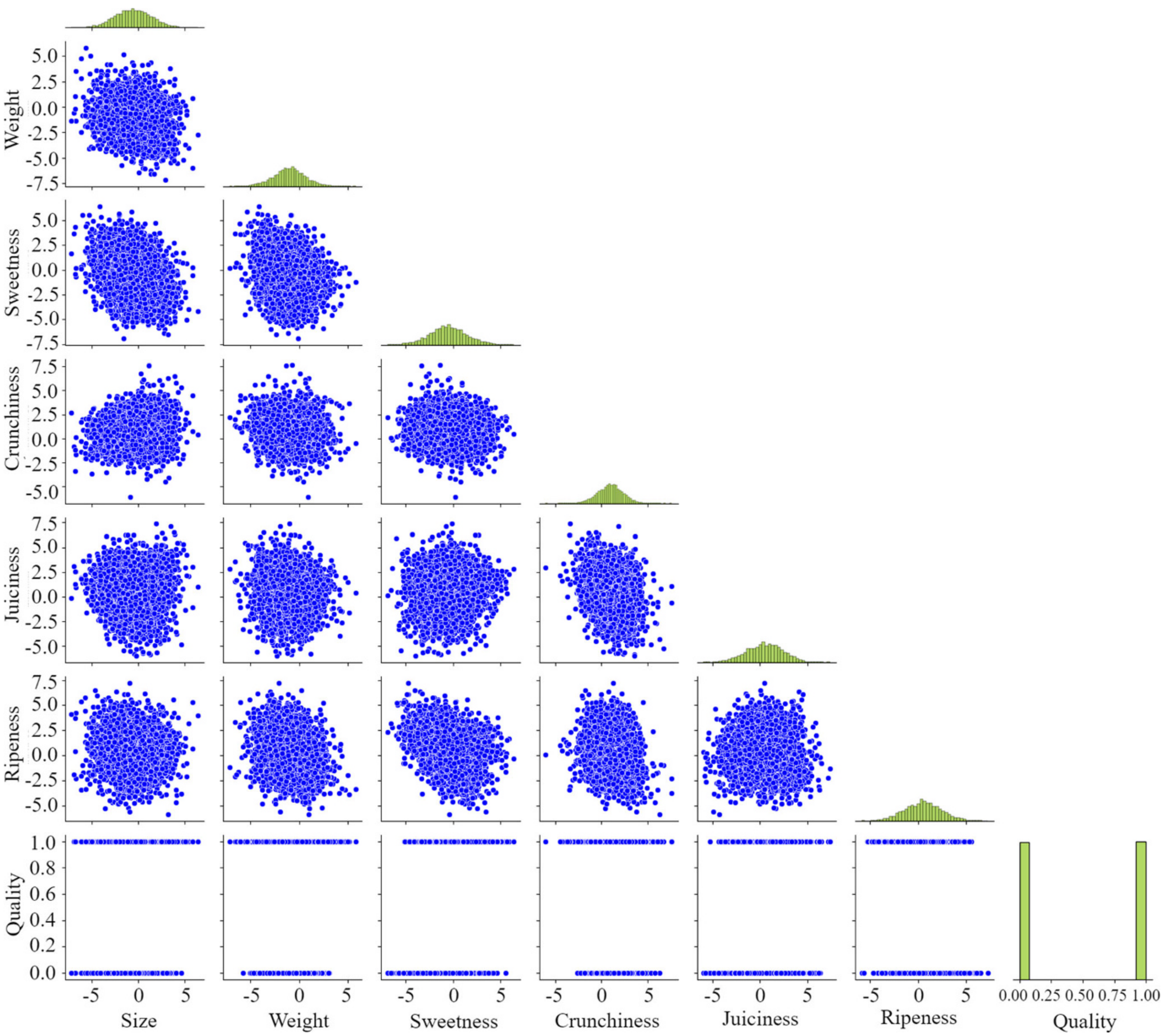

Fig. 5 Bivariate analysis results

negatives for the quality class, and 384 true positives and 18 false negatives for the low-quality class. Examining the confusion matrix of the SVM model reveals 364 true positives and 39 false negatives for the quality class, and 362 true positives and 35 false negatives for the low-quality class. The confusion matrix of the RF model, it shows 361 true positives and 45 false negatives for the quality class, and 356 true positives and 38 false negatives for the low-quality class. Evaluating the confusion matrix of the k-NN model yields 362 true positives and 45 false negatives for the quality class, and 356 true positives and 37 false negatives for the low-quality class. Lastly, the confusion matrix of the DT model exhibits 324 true positives and 77 false negatives for the quality class, and 324 true positives and 75 false negatives for the low-quality class. These results accurately reflect the classification performance of each model and provide a more comprehensive view of the evaluation criteria.

Upon examining the confusion matrix analyses, it can be observed that the MLP and SVM models can successfully predict the quality and low-quality classes, while the performance of the RF, k-NN, and DT models is lower. These findings provide valuable insights into assessing the effectiveness of various machine learning algorithms in a specific application context.

Bivariate Analysis Results

The analysis conducted based on Fig. 5 reveals weak positive or negative relationships between apple quality and

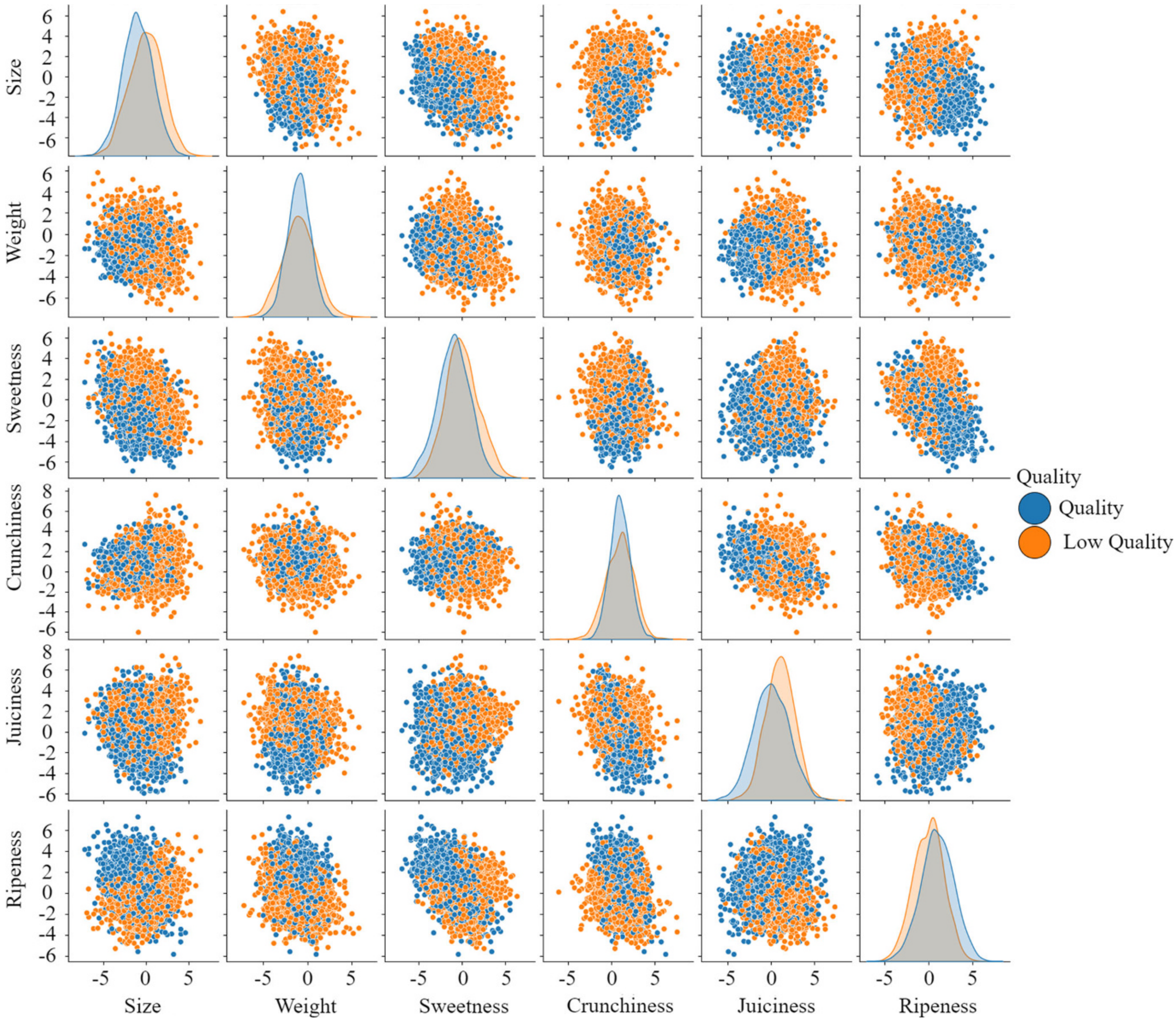

Fig. 6 Multivariate analysis results

size, sweetness, ripeness, and juiciness. However, there is no significant relationship between weight, crunchiness, acidity, and apple quality. To visualize the distribution of quality data, it is adjusted as follows: 1: quality apple, 0: low-quality apple.

An assessment of the distribution of features on quality in Fig. 5 shows that size is equally distributed across quality. Looking at weight, it is observed that there are more high-quality apples. For sweetness, an equal distribution is observed. For crunchiness, there are more quality apples. Regarding juiciness, an equal distribution is observed. For ripeness, it is observed that there are more low-quality apples.

Multivariate Analysis Results

The results of multivariate analysis allow for a more comprehensive observation of the effects on quality by considering multiple variables together. This method enables the consideration of interactions and relationships among multiple variables rather than isolating a single variable, thereby facilitating a better understanding of the complexity of factors influencing quality. The observations in Fig. 6 are explained here.

In the analysis of Fig. 6, it is observed that apples with low quality tend to be juicy and ripe. The variables of size, weight, and sweetness indicate that higher-quality apples are generally larger, heavier, and have better taste.

Recommendations and, Discussion

This study, aimed at determining apple quality, demonstrates the effective use of various machine learning classification algorithms on apple features. When examining the results obtained by using different algorithms such as MLP, SVM, RF, k-NN, and DT, the highest classification success, with an accuracy of 95.63%, was achieved with the MLP algorithm. The accuracy values of the algorithms are as follows: MLP, 95.63%; SVM, 90.75%; k-NN, 89.75%; RF, 89.63%);and DT, 81%. The recall values of the algorithms are as follows: MLP, 95.62%; SVM, 90.75%; k-NN, 89.75%; RF, 89.63%; and DT, 81%. High recall values indicate the ability of the classification model to correctly identify true positives, demonstrating its capability to minimize undesirable outcomes and not miss targeted results. When examining the correlation results, it is observed that there is no feature with a high correlation. This indicates that the features affecting apple quality are not individually highly influential, but have an effect on quality when correlated with each other. The juiciness of the apple affects its quality, while excessive juiciness can affect it negatively, leading to lower quality. These findings indicate that apple growers can actively use such machine learning models to improve the quality of their products and gain a competitive advantage in the marketing process. The results obtained emphasize the significant role that machine learning methods can play in quality control and product improvement processes in the apple industry. These models can be a valuable tool in determining quality by analyzing various characteristics of apples. Therefore, apple growers can market their products more effectively and provide consumers with more satisfying products by using these models. New studies focusing on automating these processes can be conducted by evaluating both the characteristics and images of apples together. These studies can be carried out by combining images obtained from the external appearance of the apple with data obtained from the characteristics affecting the quality of the apple. Relationships can be established between external appearance features such as color, shape, size, and internal features such as water content, acidity level. Artificial intelligence models that identify and analyze these relationships can help predict the quality of the apple.

Conclusion

Apple growers or quality control experts can use these automated systems to evaluate the quality of apples quickly and accurately. Such studies can increase efficiency in the agricultural industry and improve product quality. Representatives in the apple industry can utilize the findings from this study to incorporate machine learning methods into quality control and product improvement processes. This could not only increase growers' revenues, but also enable them to gain a competitive advantage in the industry by offering higher-quality products to consumers. This study could lay the groundwork for future research in the apple industry and encourage similar studies to be conducted.

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Author Contribution *Talha Alperen Cengel:* contributed to the conceptualization, methodology, software, validation, visualization, and writing–original draft; *Bunyamin Gencturk:* contributed to the conceptualization, methodology, software, validation, visualization, and writing–review & editing; *Elham Tahsin Yasin:* contributed to the conceptualization, methodology, validation, and formal analysis, software, as well as writing–original draft; *Muslume Beyza Yildiz:* contributed to the conceptualization, methodology, validation, and writing-review & editing; *Ilkay Cinar:* contributed to the conceptualization, methodology, formal analysis, project administration, supervision, validation and writing–review & editing; *Murat Koklu:* contributed to the conceptualization, methodology, formal analysis, project administration, supervision, validation and writing–review & editing.

Data Availability This study used a dataset from Kaggle (Elgiriyewithana 2024), and the data can be obtained through the following link: https://www.kaggle.com/datasets/nelgiriyewithana/apple-quality/discussion

Conflict of interest T.A. Cengel, B. Gencturk, E.T. Yasin, M.B. Yildiz, I. Cinar and M. Koklu declare that they have no conflicts of interests.

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