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Classification of Apple Quality Based on Physical and Chemical Properties: A Machine Learning Based Approach

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ABSTRACT

This study examines a machine learning-based approach for assessing physical and chemical properties to determine apple quality. While traditional quality control methods are time-consuming, costly, and subjective, artificial intelligence and computer vision techniques offer faster and more accurate results. The study used a dataset consisting of 4000 samples containing key physical and chemical variables such as apple size, weight, sweetness, crispness, juiciness, ripeness, and acidity. The performances of various machine learning algorithms were compared during the training and testing phases. In model performance evaluations, the Voter Classifier (VT) algorithm achieved the highest accuracy rate of 91.25% and F1-Score 91.25% also demonstrated superiority in other key metrics. In the study conducted in Trabzon, the combination of the LGBM (Light Gradient Boosting Machine) and CatBoost algorithms within the voter structure stood out as an innovative approach that increased model performance. While this method has limited applications in the literature, it has the potential to make significant contributions to the optimization of quality control processes in the agricultural sector. Therefore, it is concluded that AI-supported systems are an effective tool for agricultural quality assessment.

Elma Kalitesinin Fiziksel ve Kimyasal Özelliklere Göre Sınıflandırılması: Makine Öğrenmesine Dayalı Bir Yaklaşım

Araştırma Makalesi

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Kalite kontrol

ÖZ

Bu çalışmada elma kalitesini belirlemek için fiziksel ve kimyasal özellikleri değerlendirmek amacıyla makine öğrenmesi tabanlı bir yaklaşım incelenmiştir. Geleneksel kalite kontrol yöntemleri zaman alıcı, maliyetli ve öznelken, yapay zeka ve bilgisayarlı görme teknikleri daha hızlı ve daha güvenilir sonuçlar sunmaktadır. Çalışmada elma boyutu, ağırlığı, tatlılık, gevreklik, sululuk, olgunluk ve asidite gibi temel fiziksel ve kimyasal değişkenleri içeren 4000 örnekten oluşan bir veri seti kullanılmıştır. Eğitim ve test aşamalarında çeşitli makine öğrenmesi algoritmalarının performansları karşılaştırılmıştır. Model performans değerlendirmelerinde Seçmen Sınıflandırıcı (VT) algoritması %91,25 ile en yüksek doğruluk oranına ulaşmış ve F1 Puanı %91,25 ile diğer temel metriklerde de üstünlük göstermiştir. Trabzon'da gerçekleştirilen çalışmada, seçmen yapısı içerisinde LGBM (Light Gradient Boosting Machine) ve CatBoost algoritmalarının kombinasyonu, model performansını artıran yenilikçi bir yaklaşım olarak öne çıkmıştır. Bu yöntemin literatürde sınırlı uygulamaları olmasına rağmen, tarım sektöründe kalite kontrol süreçlerinin optimizasyonuna önemli katkılar sağlama potansiyeli bulunmaktadır. Sonuç olarak, yapay zeka destekli sistemlerin tarımsal kalite değerlendirmesinde etkili bir araç olduğu sonucuna varılmıştır.

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Introduction

Today, the agricultural sector is undergoing a major transformation with the integration of big data and artificial intelligence technologies. At the heart of this transformation are innovative approaches developed for determining and improving crop quality. In particular, the activation of quality control mechanisms in fruit varieties such as apples, which respond directly to consumer demands, provides a competitive advantage in the sector and contributes to the reduction of waste.

The determination of apple quality is traditionally a process based on human observation, which can be time-consuming, costly, and subjective. In recent years, thanks to computer vision and artificial intelligence-based systems, more objective and automated quality control methods are being developed. These systems can provide quicker and more accurate analysis by evaluating the physical characteristics of the fruit, such as color, shape, size, and texture.

Technologies such as deep learning algorithms, image processing techniques, and sensory data analysis are increasingly being used in the process of determining apple quality. These approaches have a lower margin of error compared to traditional quality control methods and ensure that consumers are offered a more consistent product. However, for these technologies to be successfully applied, proper data collection and model training are of great importance.

This study aims to examine the effectiveness of artificial intelligence-supported apple quality evaluation systems and to reveal the benefits that these systems can provide to the agricultural sector. In the following sections of the study, the advantages and disadvantages of current quality control approaches will be discussed, and the methods used to improve the performance of artificial intelligence models will be examined in detail.

Overview of Apple Quality Assessment

Importance of Quality Control in the Agricultural and Food Sector

Quality control of apples and other agricultural products is of great importance in meeting the needs of producers and consumers. Consumers expect the products they buy to meet certain quality standards, while producers aim to increase their market share by offering high-quality products. In this context, developing reliable and objective quality assessment methods has become a critical requirement.

Traditional Quality Control Methods and Limitations

Traditional methods for determining apple quality are usually based on manual inspection and sensory evaluation. However, these methods are prone to human error and may involve subjective evaluations. In addition, manual quality control processes can be time-consuming and costly. In recent years, the use of automated systems in the quality control of agricultural products has increased, and artificial intelligence techniques such as computer vision and machine learning have begun to be used effectively in quality analysis. These developments make quality control processes more economical and enable more efficient and reliable results to be achieved.

Importance of Artificial Intelligence-Based Quality Control Systems

Machine learning and deep learning-based systems have the potential to radically change quality control mechanisms in the agricultural sector. In particular, systems supported by image processing techniques can analyze the color, shape, texture, and other physical characteristics of fruits with high accuracy. These technologies provide producers with faster decision-making opportunities, while also contributing to offering consumers higher quality products. Machine learning models can process large amounts of data, optimize quality evaluation processes, and improve themselves over time. Thus, inconsistencies and human-induced errors encountered in traditional methods can be minimized, and more consistent and reliable results can be obtained.

Literature Review

Academic studies on apple quality assessment are generally based on the analysis of physical and chemical properties with the help of classifiers. Physical properties such as size, color, texture, and crispness are among the most used parameters in determining apple quality. In this context, various studies have revealed the effectiveness of different machine learning and artificial intelligence techniques.

In a study conducted by Chauhan and Singh, a 95.12% accuracy rate was achieved using the k-Nearest Neighbor (k-NN) algorithm based on physical parameters (Singh Chauhan et al. 2012). Similarly, Yin et al. developed a two-branch model based on physical features such as shape, texture, and contour, achieving high accuracy rates (Yin et al. 2022). Mureșan revealed that multivariate analyzes play a critical role in the quality assessment of apple genotypes (Mureşan, 2022). Furthermore, Hu et al. achieved a 95.49% success rate using classifiers based on physical features (Hu, 2021). In Sabanci's study, it was reported that apple varieties were classified with a 98.88% success rate using k-NN and Artificial Neural Networks (MLP) (Sabanci and Unlersen, 2016). Models based on physical quality parameters also yield successful results, especially in the evaluation of maturity levels. Ashok and Vinod performed the separation of rotten and healthy apples with a Probabilistic Neural Network (PNN) (Ashok and Vinod, 2014). Renjith and MA showed that machine learning and deep learning techniques are effective in increasing the classification performance based on maturity levels (Muthulakshmi and Renjith, 2021). Li et al. successfully classified apple quality with a 95.33% accuracy rate using Convolutional Neural Networks (CNN) (Li et al. 2021). Moallem et al. achieved high accuracy rates in the classification of golden delicious apples with computer vision methods based on surface features (Moallem et al. 2017). Mehinagic et al. revealed that quality characteristics such as crispness and fruit juice content can be successfully predicted by physical measurements (Mehinagic et al. 2004). Zhu et al. evaluated apple quality with a 90.6% accuracy rate using Gabor features and kernel principal component analysis (KPCA) (Zhu et al. 2007). Ma et al. achieved an 80% accuracy rate by analyzing red Fuji apples with near-infrared spectroscopy (Ma and Zhang, 2019). Cliff and Bejaei revealed that physical properties can accurately predict sensory properties such as apple hardness and crispness (Cliff and Bejaei, 2018). Corollaro developed a hybrid model that evaluates apple quality with sensory and instrumental measurements (Corollaro, 2014). Adebayo and Hashim classified pear maturity stages using laser imaging and artificial neural networks and stated that this method could be successful in apple classification as well (Adebayo and Hashim, 2021). Zhang developed a model that compensates for the differences in maturity levels and showed that apple quality can be accurately determined (Zhang, 2022).

In recent years, various non-destructive methods have been developed to assess apple quality. For example, hyperspectral imaging (HSI) combined with Partial Least Squares Regression (PLSR) has been shown to accurately predict internal quality parameters such as soluble solid content (SSC), firmness, and starch index (Hasanzadeh et al., 2022). The combination of visible and near-infrared hyperspectral imaging (Vis/NIR HSI) with artificial neural networks (ANN) also predicts SSC and firmness during storage with high R^2 values (Sharma et al., 2023). Convolutional neural networks (CNN) trained on a narrow spectral band (660 nm) classify apple surface defects with near-perfect accuracy, enabling cost-effective quality control (Classification of Defective and Non-Defective Products Using Convolutional Neural Networks in Quality Control, 2023). Mask Region-based CNN (Mask R-CNN) approaches enable high F1-score apple detection and segmentation in orchards, supporting automated harvesting systems (Wang and He, 2022). The occlusion-aware object recognition network (O2RNet) achieves accurate apple detection in clustered and shaded orchard environments (Li et al., 2021). Lightweight detection object models combined with generative adversarial networks (LightDOM-GAN) and attention mechanisms provide high accuracy and real-time performance for maturity and damage detection (Wang et al., 2022). Visible spectroscopy combined with particle swarm optimization (PSO) and back propagation neural networks (BPNN) models achieves very high correlation and low error rates in SSC prediction (Peng et al., 2023).

Analysis shows that existing studies have generally been conducted using a single classification algorithm or a limited number of physical/chemical properties. This limits model performance and generalizability.

These studies show that the evaluation of physical properties with machine learning algorithms enables high accuracy rates to be achieved in the prediction of apple quality. However, the comparison of different methods and the examination of new model development processes will contribute to further improvement of apple classification systems.

In contrast, this study demonstrates that combining the LGBM and CatBoost algorithms in a hybrid framework and utilizing a rich feature set yields both a significant increase in accuracy and strengthens the model's generalizability.

In this study, the effectiveness of artificial intelligence-supported classification methods will be analyzed in line with the approaches presented in the existing literature.

Material and Methods

In this study, the dataset (Kaggle, 2025) used for apple quality analysis consists of samples containing various physical and chemical properties. The dataset contains a total of 4000 samples, and includes the following variables for each apple:

I. A_id: Unique identification number assigned to each apple sample.

II. Size: A variable indicating the size of the apple.

III. Weight: A measurement representing the weight of the apple.

IV. Sweetness: A value indicating the sweetness level of the apple.

V. Crunchiness: A variable indicating the crispness level of the apple.

VI. Juiciness: A measurement showing the juiciness rate of the apple.

VII. Ripeness: A variable indicating the ripeness level of the apple.

VIII. Acidity: A measurement expressing the acidic structure of the apple.

IX. Quality: A categorical variable expressing the general quality status of the apple ("good" or "bad").

The dataset contains the physical and chemical properties of apples classified according to various quality criteria and is used for studies on apple quality estimation and analysis.

As with every machine learning algorithm, the dataset needs to be preprocessed beforehand. These preprocessing operations have removed the “A_id” column, which holds the number of each apple. In case the “Acidity” column cannot be converted to a number, those that cannot be converted to a number have been changed to “NaN”. Repeated rows have been queried and removed from the dataset. Then, variable distributions have been examined. The density graphs used for this examination are shown in Figure 1.

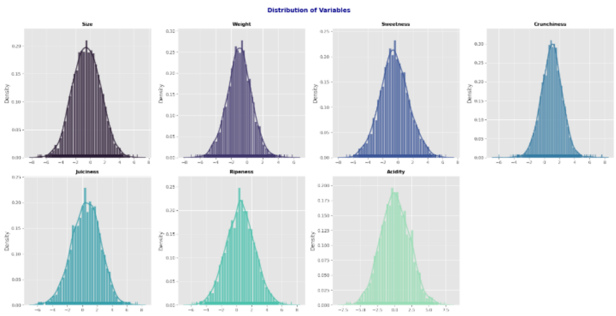

Figure 1. Distribution of numerical variables

In addition, QQ (Quantile-Quantile) plots were used to understand and visualize how well the distribution of a dataset conforms to the theoretical normal distribution. These graphs are presented in Figure 2.

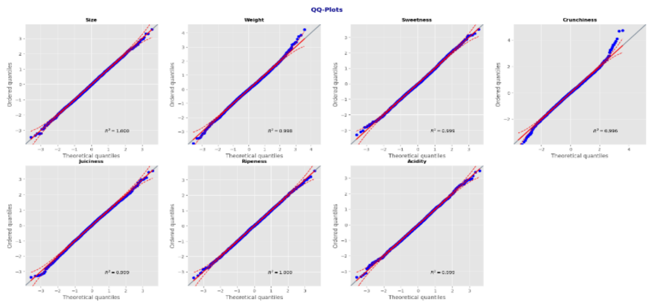

Figure 2. QQ plots of numerical variables

In Figure 2, the blue dots for all variables are largely located on the straight gray line, which indicates that the data is very close to a normal distribution. In addition, the R^2 (coefficient of determination) values range from 0.996 to 1.000, which indicates that the data conforms to the normal distribution to a high degree. Slight deviations can be observed in some variables (e.g., Weight and Crunchiness) at extreme values, but in general, these deviations are at a negligible level. QQ plots show that the variables used in apple quality analysis fit the normal distribution quite well.

Table 1 shows that $p > 0.05$ was found for Size, Sweetness, Ripeness, and Acidity, indicating that these variables are normally distributed. $P \leq 0.05$ was found for Weight, Crunchiness, and Juiciness, indicating that these variables are not normally distributed. This indicates that parametric or nonparametric tests should be selected in analysis based on the distributional properties of these variables. Parametric tests can be misleading for variables that do not exhibit a normal distribution, so alternative nonparametric methods should be preferred. The D'Agostino-Pearson test allows you to determine whether the variables in question are normally distributed based on the p values in Table 1.

Table 1. Normality Test: D' Agostino and Pearson

	p_value	Distribution
Size	0.552	Normal Distribution
Weight	0.000	No Normal Distribution
Sweetness	0.094	Normal Distribution
Crunchiness	2.198	No Normal Distribution
Juiciness	0.013	No Normal Distribution
Ripeness	0.635	Normal Distribution
Acidity	0.166	Normal Distribution

The “Quality” column, which is a categorical decision variable, is also shown in Figure 3 because its distribution is important.

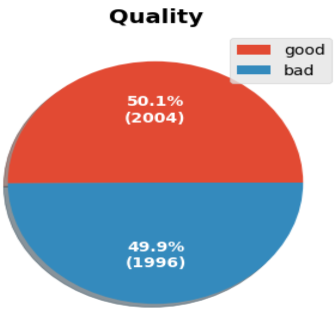

Figure 3. Distribution of "quality" variable

This graph shows the distribution of the samples in the dataset in terms of quality. The proportion of data divided into two classes, “good” and “bad”, is quite balanced. Samples belonging to the “good” class make up 50.1% of the total dataset (2004 samples), while samples belonging to the “bad” class make up 49.9% (1996 samples). This suggests that it creates a balanced dataset for the classification models and that the learning algorithms have a low risk of encountering overfitting or imbalanced dataset problems.

The relationship between numerical variables is shown as a scatter plot in Figure 4.

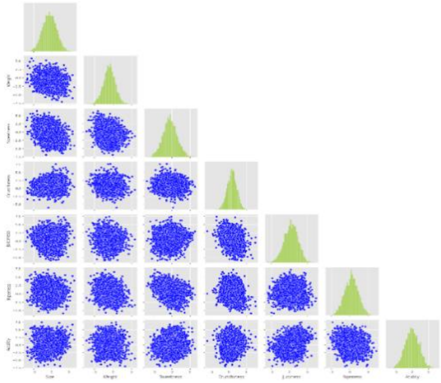

Figure 4. Scatter plot between numeric variables

Figure 4 is a scatter plot and histogram matrix created to analyze the relationships between the variables in the dataset. The histograms on the diagonal axis represent the distribution of each variable, while the scatter plots in the other cells visualize the relationship between pairs of variables. In general, there are no clear linear relationships between variables, although there are low correlations between some variables. This visualization is important for analyzing the interaction between variables and evaluating the overall structure of the dataset.

The correlation between numerical variables is shown with a heat map in Figure 5.

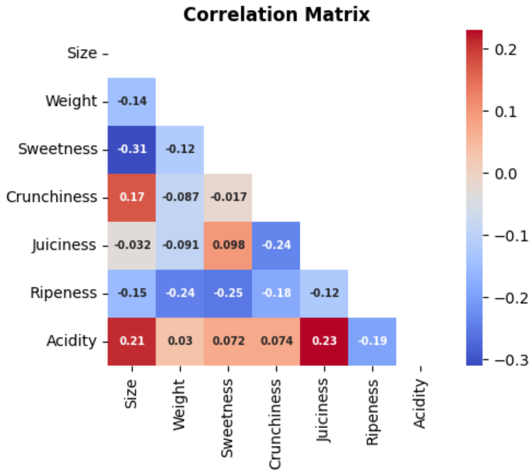

Figure 5. Correlation matrix between numeric variables

The correlation matrix in Figure 5 shows Pearson correlation coefficients to measure linear relationships between variables in the data set. Red tones on the colour scale indicate positive correlation, while blue tones indicate negative correlation. In general, there are no strong correlations between variables, which indicates that the features in the data are largely independent of each other. Specifically, there is a moderate negative correlation of -0.31 between ‘Size’ and ‘Sweetness.’ This indicates that as the size of the apple increases, the sweetness level tends to decrease. In other words, larger apples may be less sweet. This relationship should be carefully evaluated, as it could potentially impact product quality or taste profile. Additionally, there is a weak negative correlation of -0.19 between ‘Acidity’ and ‘Ripeness.’ This indicates that as an apple ripens, its acidity tends to decrease slightly. This relationship between ripeness and acidity may provide important insights into the product's taste and storability. Furthermore, the low correlations across the matrix suggest that the variables are relatively independent of each other, meaning that there is a low likelihood of these variables causing multicollinearity or high multicollinearity issues during the data preprocessing stage. When using such independent variables in machine learning models or statistical analysis, it means that each feature can provide distinct contributions specific to the dataset. Correlation analysis serves as an important guide both in understanding potential relationships between variables and in determining which factors should be considered during data preprocessing and modelling stages. The observed negative relationship between size and sweetness can be considered in quality assessments or consumer preference analysis. Additionally, the relationship between acidity and ripeness can help understand how ripeness levels affect taste. Such information holds value for both product development and market strategies.

The violin graph showing the relationship of each of the numerical variables with the "Quality" variable is shown in Figure 6.

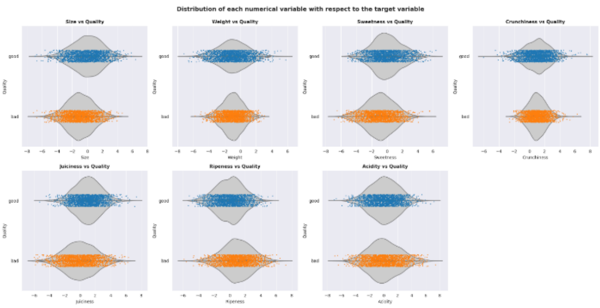

Figure 6. Distribution of each numerical variable with respect to the target variable

Figure 6 shows the distribution of various physical and sensory attributes that determine apple quality (size, weight, sweetness, crispness, crunchiness, juiciness, ripeness, and acidity) in relation to the quality variable (good/bad). In each sub-graph, the distribution of the relevant variable is visualized in two different classes as "good" and "bad", and the densities of the data points are supported by violin plots. When the graphs are analyzed, it is observed that high quality apples are generally differentiated in certain physical and sensory characteristics. Sensory characteristics such as sweetness, crispness, and juiciness are more pronounced for high quality apples. This analysis provides an important visualization to understand how the key factors determining apple quality are statistically distributed and helps to understand which variables machine learning models can give more importance when predicting quality.

Results and Discussion

The "Quality" column, which will be used as the target in the classification, was removed, and the data was converted into a binary structure by selecting 0 for the "Bad" expression and 1 for the "Good" expression.

The training and test datasets were divided as 80% (3600 samples) and 20% (800 samples). Then: Within the VT, the voters of the LGBM and CatBoost algorithms were defined. The training VT, LR, RF, ET, XGB, LGBM, CatBoost, SVC, and GaussianNB classifiers were comparatively examined. Performance graphs are shown in Figure 7.

Explanation and Breakdown

Data Preprocessing

The "Quality" column, which indicates whether an apple is "Good" or "Bad," is transformed into numerical values (0 and 1) for machine learning algorithms to process. The dataset is split into training (80%) and testing (20%) sets. This is crucial to evaluate how well the trained models perform on unseen data.

Voter Classifier (Ensemble Method)

A "Voter" classifier is created, which combines the predictions of multiple individual classifiers. In this case, it combines LGBM and CatBoost algorithms. Ensemble methods often improve overall prediction accuracy.

The reason for using LGBM and CatBoost together in the voting algorithm is that both algorithms are powerful gradient boosting-based models and offer complementary advantages. LGBM is a fast and lightweight boosting algorithm developed by Microsoft. It stands out for its high processing speed, low memory usage, and parallel learning capabilities in large datasets. It is also preferred for its parameter optimization and ability to achieve high accuracy on large datasets. CatBoost, on the other hand, is a boosting algorithm that works particularly well with categorical data. It is chosen for its ability to work directly on categorical data without the need for preprocessing, its use of special regularization techniques to prevent overfitting, and its balanced performance. The combined use of these two algorithms in VotingClassifier reduces variations that arise in different data structures and problems, resulting in a more generalizable, balanced, and high-performance model. This provides advantages such as speed, accuracy, and reduced risk of overfitting. Additionally, by nature of ensemble methods, the combined use of multiple powerful models increases the stability and overall success of the results. The selection of LGBM and CatBoost was influenced by their distinct yet complementary strengths, including speed, accuracy, categorical data processing capabilities, and overfitting prevention. The combination of LGBM's speed and efficiency with CatBoost's strengths in category processing and overfitting control aims to achieve superior and balanced classification performance through the Voting algorithm.

Compared Classifiers

The study compares the performance of the Voter classifier with several other well-known machine learning algorithms: LR, RF, ET, XGB, LGBM, CatBoost, SVC, GaussianNB.

Performance Evaluation

The performance of all these classifiers is probably evaluated using metrics such as accuracy. Figure 7 refers to a visual representation comparing the performance of these classifiers.

Additional Notes

This text snippet describes a common machine learning workflow: data preprocessing, model training, and evaluation. The choice of specific algorithms (LGBM, CatBoost, etc.) suggests that the authors are likely dealing with a dataset where these algorithms are shown good performance in similar tasks. Comparing multiple classifiers is a good practice to select the best-performing model for the given problem.

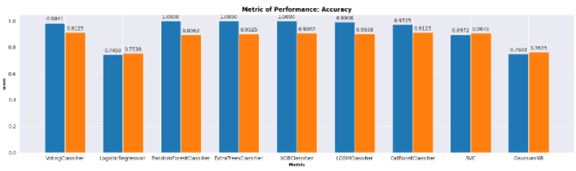

Figure 7. Metric performance: Accuracy (Train & Test)

Figure 7 compares the accuracy performance of various machine learning models on training (blue) and test (orange) datasets. It is observed that ensemble models such as XGB, RF, and ET achieve 100% accuracy on training data, but exhibit relatively lower accuracy on test data. This is due to a possible overfitting problem. Simpler models such as LR and GaussianNB are more balanced on both training and test data but have relatively lower accuracy rates. Figure 7 helps analyze the generalization capabilities of models and reveals that some models show high accuracy in training but lose performance on test data.

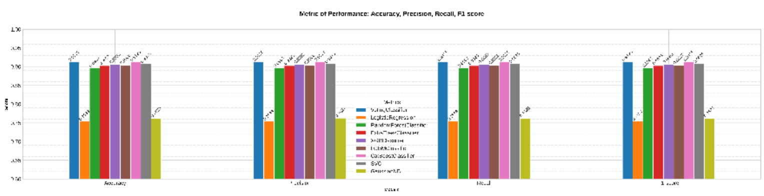

Figure 8. Metrics of test performance

Figure 8 compares the performance of different machine learning classification algorithms, and the VotingClassifier method achieved the highest success in all metrics

(91.25% accuracy, precision, sensitivity, and F1-score). Other advanced models (RandomForest, ExtraTrees, XGBoost, LGBM, CatBoost, SVC) showed similar and high performance, while Logistic Regression and GaussianNB models achieved relatively lower results. Balanced and consistent performance was observed across all metrics, which supports the model's overall success. However, the fact that the model has not been tested on different datasets and that real-time system integration has not yet been performed limits the generalizability and practical applicability of the study. In the future, the model's performance should be improved through parameter optimization, evaluation on different datasets, and system integrations.

The numerical values of the test data are shown in Table 2.

Table 2. Metric of test performance: Accuracy, precision, recall, F1-Score Table (%)

Models	Test Accuracy	Precision	Recall	F1-Score
VT	91.250	91.26	91.25	91.25
CatBoost	91.250	91.27	91.25	91.25
SVC	90.750	90.75	90.75	90.75
XGB	90.625	90.63	90.62	90.63
LGBM	90.375	90.38	90.38	90.37
ET	90.250	90.25	90.25	90.25
RF	89.625	89.64	89.62	89.62
GaussianNB	76.250	76.27	76.25	76.24
LG	75.380	75.38	75.38	75.37

As can be understood from Table 2, the best performance among the models was achieved by VT. VT, which is a combination of LGBM and CatBoost due to its structure, is followed by the CatBoost algorithm.

The voter classifier model developed in this study, based on LGBM and CatBoost, has the potential to be integrated into real-time quality control systems, as it enables the fast and reliable determination of apple quality with a high accuracy rate (91.25%). Such integration would enable the instant classification of fruits on production lines or in packaging facilities and the rapid separation of low-quality products. For the model to operate efficiently in real-time applications, hardware components such as high-resolution camera sensors, industrial PCs, or embedded GPU units (e.g., NVIDIA Jetson), and GigE or USB 3.0 connections for fast data transfer are required. On the software side, it is important to convert the model to ONNX format based on Python, optimize it with real-time inference libraries such as TensorRT or OpenVINO, and perform image processing steps with low latency. Additionally, to enhance the system's resilience against different varieties, lighting conditions, and seasonal variations, the training data must be periodically updated, and the model must be retrained. If these technical requirements are met, the proposed method could offer an effective solution to enhance both efficiency and product quality in agricultural production processes.

Conclusion

In this study, the effectiveness of machine learning-based classification systems in evaluating apple quality has been comprehensively and systematically demonstrated. The findings show that AI-supported approaches make processes quicker and more reliable outcomes compared to traditional quality control methods. In particular, it is noteworthy that the VT (Voting) algorithm, which achieved the highest success rate of 91.25%, provides effective classification performance through the integration of different machine learning models using the ensemble method. This supports the superiority of ensemble learning over individual models and its potential to increase model stability. The study's findings emphasize that AI-based systems can play a strategic role in improving quality control processes and reducing food waste in the agricultural sector. Future research should focus on increasing the generalizability of models by testing them on different and heterogeneous datasets, further improving algorithm performance through hyperparameter optimization, and developing alternative feature engineering techniques for data characteristics. This will enable both model accuracy and the expansion of application areas, thereby increasing the effectiveness and acceptance of artificial intelligence solutions in sectoral applications.

Summary of the Study: This study has shown how effective machine learning-based classification systems are for assessing apple quality. It has been determined that compared to traditional methods, AI-supported systems provide faster, more accurate results.

Best Performance: The VT (Voter) algorithm performed best with an accuracy rate of 91.25%. This means that better results are achieved by combining multiple machine learning algorithms.

Importance of Artificial Intelligence: The results emphasize how important it is to use AI-based systems to improve quality control processes and reduce waste in the agricultural sector.

Future Work: Tests will be conducted on different and heterogeneous data sets to increase the generalizability of the models. Thus, the model will be able to perform successfully not only on a specific data set but also under various conditions. Additionally, improving the performance of algorithms through parameter optimization is a key objective. Since machine learning algorithms have numerous configuration parameters, optimizing these parameters correctly can significantly enhance model success. Furthermore, the f-fold cross-validation method will be integrated to assess the consistency and stability of the model across different data partitions. F-fold validation will reveal the variability in the model's performance, enabling more reliable and generalizable results to be obtained. Thus, both parameter optimizations and cross-validation methods will increase the accuracy and robustness of the model.

Alternative feature engineering techniques can be developed. Feature engineering is the process of uncovering important information in data and improving the model. The success of the model can be increased by trying different techniques.

Generalizability: The ability of a model to perform well on different and similar data other than the training data.

Parameter Optimization: In comparing machine learning algorithms, the default parameters of the Sklearn library were used to ensure that no model gained an unfair advantage over another. While Sklearn's default parameters are suitable for understanding the fundamental operation of the algorithms and for basic comparisons, it is known that these parameters do not guarantee optimal performance. Therefore, in the current study, performance evaluations were conducted using these baseline parameters, ensuring that all models were evaluated on equal footing. Future work plans to utilize hyperparameter optimization to improve model performance. Because the impact of hyperparameters in the Sklearn library varies depending on data preprocessing and model characteristics, the importance of this optimization is frequently emphasized in the literature. The Sklearn default parameters provide a baseline for comparison; however, it is expected that model performance will be significantly improved with parameter optimization in later stages.

Advantages and Disadvantages of the Study: This study offers advantages such as high accuracy, balanced dataset usage, and low risk of overfitting. However, the model has not been tested on different datasets, and real-time system integration has not been performed. These limitations restrict the generalizability of the study's results and their validity in practical applications. Therefore, future research should aim to address these shortcomings.

Feature Engineering: The process of creating new features from raw data that will allow machine learning algorithms to perform better.

Conflict of Interest

The authors declare no conflict of interest.

Authors' Contributions

The authors declare that they have contributed equally to the article.

References

Adebayo SE, Hashim N., 2021. Prediction of quality attributes and maturity classification of pear fruit using laser imaging and artificial neural network. Food Res, 5(1): 144–151.

Apple Quality., 2025. Available: kaggle.com/datasets/nelgiriyewithana/apple-quality

Ashok V, Vinod DS., 2014. Automatic quality evaluation of fruits using Probabilistic Neural Network approach. International Conference on Contemporary Computing and Informatics (IC3I), IEEE, 308–311.

Cliff MA, Bejaei M., 2018. Inter-correlation of apple firmness determinations and development of cross-validated regression models for prediction of sensory attributes from instrumental and compositional analyse. Food Research International, 106: 752–762.

Corollaro ML., 2014. A combined sensory-instrumental tool for apple quality evaluation. Postharvest Biol Technol, 96: 135-144.

Hasanzadeh B, Abbaspour-Gilandeh Y, Soltani-Nazarloo A, Hernández-Hernández M, Gallardo-Bernal I, Hernández-Hernández JL., 2022. Non-destructive detection of fruit quality parameters using hyperspectral imaging, multiple regression analysis and artificial intelligence. Horticulturae, 8(7): 598.

Hu G., 2021. Infield apple detection and grading based on multi-feature fusion. Horticulturae, 7(9): 276.

Li Y, Feng X, Liu Y, Han X., 2021. Apple quality identification and classification by image processing based on convolutional neural networks. Scientific Reports, 11: 16618.

Ma L, Bi S, Zhang C., 2019. Apple grading system based on near infrared spectroscopy and evidential classification forest. International Conference on Advanced Mechatronic Systems (ICAMechS), IEEE, 326–330.

Mehinagic E, Royer G, Symoneaux R, Bertrand D, Jourjon F., 2004. Prediction of the sensory quality of apples by physical measurements. Postharvest Biol Technol, 34(3): 257–269.

Moallem P, Serajoddin A, Pourghassem H., 2017. Computer vision-based apple grading for golden delicious apples based on surface features. Information Processing in Agriculture, 4(1): 33–40.

Mureșan AE., 2022. Chemometric comparison and classification of 22 apple genotypes based on texture analysis and physico-chemical quality attributes. Horticulturae, 8(1): 64.

Muthulakshmi A, Renjith PN., 2021. Comprehensive systematic review on fruit maturity detection technique. Second International Conference on Electronics and Sustainable Communication Systems (ICESC), IEEE, 1234–1240.

Patil R, Thigale S, Karve S, Kale V., 2023. Classification of defective and non-defective products using convolutional neural networks in quality control. Science and Engineering, 11(1): 213–222. https://doi.org/10.52783/cienceng.v11i1.115

Peng W, Ren Z, Wu J, Xiong C, Sun B, Liang G, Zhou M., 2023. Qualitative and quantitative assessments of apple quality using Vis spectroscopy combined with improved particle-swarm-optimized neural networks. Foods, 12(10): 1991.

Sabanci K, Ünlerşen MF., 2016. Different apple varieties classification using kNN and MLP algorithms. IJISAE, 4: 166–169.

Sharma S, Sirisomboon P, Sumesh KC, Terdwongworakul A, Phetpan K, Kshetri TB, Sangwanangkul P., 2023. Near-infrared hyperspectral imaging combined with machine learning for physicochemical-based quality evaluation of durian pulp. Postharvest Biology and Technology, Postharvest Biology and Technology, 200: 112334.

Singh Chauhan AP, Partap Singh A., 2012. Intelligent estimator for assessing apple fruit quality. Int J Comput Appl, 60(5): 35-41.

Wang D, He D., 2022. Apple detection and instance segmentation in natural environments using an improved Mask Scoring R-CNN Model. Frontiers in Plant Science, 13: 1-15.

Wang F, Zhao C, Yang H, Jiang H, Li L, Yang G., 2022. Non-destructive and in-site estimation of apple quality and maturity by hyperspectral imaging. Computers and Electronics in Agriculture, 195: 106843.

Yin J, Geng L, Guo Y, Huang Y, Song Y, Zhao H., 2022. Apple appearance quality classification method based on double branch feature fusion network. Cognitive Computation and Systems, 4(3): 284–293.

Zhang M., 2022. Modification of the effect of maturity variation on nondestructive detection of apple quality based on the compensation model. Spectrochim Acta A Mol Biomol Spectrosc, 267: 120598.

Zhu B, Jiang L, Luo Y, Tao Y., 2007. Gabor feature-based apple quality inspection using kernel principal component analysis. J Food Eng, 81(4): 741-749.