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Research article

Predicting Wine Quality Based on Features Using Naive Bayes Classifier

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ABSTRACT

This study explores the application of the Naive Bayes classifier in predicting wine quality based on physicochemical attributes. Leveraging a dataset containing features such as acidity, pH, alcohol content, and sulfur dioxide concentrations, the research aims to address the limitations of traditional sensory evaluation methods, which are often subjective and inconsistent. Data preprocessing, including normalization and feature selection, is performed to ensure the dataset is suitable for machine learning. The Naive Bayes classifier is implemented using Python's scikit-learn library, with hyperparameter tuning conducted to optimize its performance. The model is evaluated on metrics such as accuracy, precision, recall, and F1-score, achieving competitive results compared to other machine learning techniques such as Decision Trees and Support Vector Machines. The findings demonstrate the Naive Bayes classifier's efficiency in handling high-dimensional data, its computational simplicity, and its potential for real-time quality assessment in the wine industry. This research highlights the role of machine learning in automating and enhancing quality control processes, contributing to the broader integration of data-driven approaches in the agri-food sector. The study underscores the feasibility of using physicochemical features as objective indicators of wine quality, offering a scalable and cost-effective alternative to traditional methods.

1. Introduction

The wine industry plays a significant role in the global agri-food sector, contributing notonly to the economy but also to cultural and social experiences. As consumers' preferences evolve, maintaining consistent wine quality has become a top priority for producers aiming to stand out in a competitive market. Quality is one of the most critical factors determining consumer satisfaction, influencing purchasing decisions, brand loyalty, and overall market trends. Traditionally, the evaluation of wine quality has relied heavily on sensory analysis conducted by expert tasters. This approach, although insightful, is inherently subjective, labor-intensive, and expensive. It is also prone to variability due to individual biases and external environmental factors, which can lead to inconsistencies in quality assessment (Nachev et al., 2021) [1].

To overcome these challenges, there has been a growing shift toward objective, data-driven methodologies that leverage advanced analytical techniques and machine learning (ML). By focusing on measurable physicochemical properties, such as acidity, residual sugar, pH, alcohol content, and sulfur dioxide concentrations, researchers can develop predictive models capable of automating the quality assessment process (Patel and Mehta, 2023) [2]. These features, which are strongly correlated with sensory perceptions of quality, serve as reliable indicators that facilitate a more consistent and reproducible evaluation framework.

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Among the array of machine learning techniques available, the Naive Bayes classifier has emerged as a promising approach for predictive modeling in the wine industry. The Naive Bayes algorithm operates on the principle of Bayes' theorem and assumes conditional independence among input features. While this assumption is not always met in complex, real-world datasets, the algorithm has proven to be highly effective in classification tasks across various domains, including text classification, spam detection, medical diagnosis, and more recently, wine quality prediction (Chen et al., 2022) [3]. Its advantages include computational efficiency, simplicity in implementation, and the ability to handle high-dimensional data, making it suitable for both research and practical applications[4].

In the context of wine quality prediction, the Naive Bayes classifier is particularly appealing due to its low computational overhead and interpretability. These characteristics make it ideal for deployment in resource-constrained environments and real-time decision-making processes, such as in wineries or quality control facilities. By analyzing physicochemical data, the model can classify wines into predefined quality categories, providing valuable insights to winemakers regarding production adjustments and market positioning [5].

The integration of machine learning into the wine industry reflects a broader trend toward digitization and automation in agriculture. As datasets containing chemical and sensory attributes of wine become more accessible, there is a growing opportunity to apply sophisticated ML models to enhance both product quality and operational efficiency. Recent studies have demonstrated that predictive models, such as those based on Naive Bayes, not only improve the accuracy of quality assessments but also offer scalability and cost-effectiveness compared to traditional sensory evaluations [6].

2. Materials Methods

The methodology for this research focuses on developing a robust and efficient framework for predicting wine quality using physicochemical properties extracted from the provided dataset. This dataset, comprising features such as acidity, alcohol content, and sulfur dioxide concentrations, serves as the basis for training and testing a Naive Bayes classifier. The choice of this algorithm is motivated by its simplicity, computational efficiency, and suitability for classification tasks involving high-dimensional data [1]. By leveraging these objective metrics, the study aims to address the inherent limitations of traditional sensory evaluation methods, which are often subjective, resource-intensive, and prone to inconsistencies [2].

Data preprocessing is a critical first step, involving handling missing values, normalizing features, and encoding categorical variables to ensure compatibility with the Naive Bayes algorithm. The dataset is then split into training and testing subsets using an 80-20 stratified split to preserve class distribution [3].

Feature selection techniques, such as correlation analysis, are employed to identify the most influential predictors of wine quality, enhancing model interpretability and performance [4].The Naive Bayes classifier is implemented using Python's scikit-learn library, with hyperparameter tuning performed via grid search and cross-validation to optimize the model's accuracy. Performance metrics, including accuracy, precision, recall, and F1-score, are calculated to evaluate the classifier's predictive capabilities. Additionally, the study compares the Naive Bayes classifier with other machine learning algorithms, such as Decision Trees and Support Vector Machines, to highlight its relative strengths and limitations in predicting wine quality [5][6].

2.1. Data Collection

The dataset used in this research, sourced from publicly available repositories, includes physicochemical attributes such as fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, alcohol, and quality scores. These attributes serve as independent variables, while the quality score (ranging from 0 to 10) represents the dependent variable [7]. The data is divided into an 80-20 stratified split to ensure balanced representation of all quality levels across training and testing subsets [8].

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2.2. Data Preprocessing

To ensure the dataset is suitable for modeling, preprocessing steps are conducted. Missing values are addressed using imputation techniques or by removing incomplete records based on their impact on data integrity. Normalization is applied to scale continuous variables, ensuring compatibility with the Naive Bayes algorithm. Additionally, outliers are identified and handled during Exploratory Data Analysis (EDA) to enhance model performance [9].

2.3. Feature Selection and Analysis

Feature selection techniques, such as correlation analysis and Recursive Feature Elimination (RFE), are employed to identify the most relevant predictors of wine quality. This step improves the model's interpretability and reduces computational complexity. For instance, attributes like alcohol content and volatile acidity are known to strongly influence wine quality and are prioritized during feature selection [10].

Correlation analysis is often the first step in understanding the linear relationships between input features and the target variable. By calculating Pearson or Spearman correlation coefficients, researchers can assess how strongly each feature correlates with wine quality scores. Features with high absolute correlation values such as alcohol (positively correlated) and volatile acidity (negatively correlated) are flagged as significant contributors. However, correlation alone may overlook non-linear or multivariate interactions, prompting the need for more sophisticated methods such as RFE.

Recursive Feature Elimination works by fitting a model and recursively removing the least significant feature based on its contribution to the model's predictive power. This method is particularly effective when paired with algorithms like Random Forests or Support Vector Machines, which can provide robust estimates of feature importance. In the context of wine quality prediction, RFE might reveal that although some features like citric acid or residual sugar have lower direct correlation with the target, their interaction with other variables still holds predictive value justifying their retention in the final model.

Another valuable method for feature analysis is mutual information, which measures the amount of shared information between a feature and the target variable, regardless of the nature of their relationship (linear or non-linear). This is especially useful in datasets where underlying relationships may not be captured well by correlation coefficients. For example, sulfur dioxide levels might have a subtle but meaningful impact on perceived wine quality only when combined with specific ranges of pH or alcohol content. Identifying such hidden patterns strengthens the model's overall accuracy and generalization capabilities.

Dimensionality reduction techniques like Principal Component Analysis (PCA) can also be employed alongside feature selection to transform and compress the dataset into uncorrelated components that retain the majority of the variance. While PCA reduces dimensionality, it often sacrifices interpretability, which may be a drawback when model transparency is a priority. Therefore, feature selection is usually preferred in applications where understanding the influence of specific attributes such as acidity levels or chlorides on wine quality is important for decision-making by vintners, quality control teams, or marketing strategists.

By refining the set of input variables, feature selection not only improves the efficiency and performance of machine learning models but also enhances domain insights. For instance, identifying alcohol content as a strong positive influencer of wine quality may prompt wineries to adjust fermentation processes or labeling strategies to meet consumer expectations. Similarly, recognizing the negative impact of high volatile acidity could drive quality control efforts in the production pipeline. Ultimately, effective feature selection serves both computational and practical purposes, bridging the gap between data science and real-world decision-making in the wine industry.

2.4. Model Development

The Naive Bayes classifier is chosen due to its ability to handle high-dimensional data efficiently. The Gaussian variant of the algorithm is implemented using Python's scikit-learn library, as it is well-suited for continuous features. Hyperparameter tuning is performed using grid search and k-fold cross-validation to optimize parameters such as smoothing factors, ensuring a balance between bias and variance [11].

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2.5. Performance Evaluation and Comparison

The model's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve. These metrics provide a comprehensive assessment of the model's predictive capabilities. To contextualize its performance, the Naive Bayes classifier is compared with other algorithms, including Decision Trees and Support Vector Machines (SVM). The comparative analysis highlights the Naive Bayes classifier's efficiency and areas for improvement [12].

Accuracy serves as an initial indicator of overall model performance, reflecting the proportion of correct predictions across all classes. However, in imbalanced datasets where one class may significantly outnumber others accuracy alone can be misleading. Precision and recall offer a more nuanced understanding. Precision evaluates the model's ability to avoid false positives, making it particularly important in contexts where incorrect positive predictions carry high costs. Conversely, recall assesses the model's sensitivity in capturing true positives, which is crucial when missing relevant cases can have serious consequences. The F1-score, which harmonically balances precision and recall, is often used to evaluate the trade-off between these two aspects, especially when an even balance is desired.

The ROC (Receiver Operating Characteristic) curve and its associated area under the curve (AUC) further enhance the evaluation by illustrating the model's ability to discriminate between classes across different threshold values. A higher AUC value indicates that the model is better at distinguishing between positive and negative classes, making it a critical measure for classification tasks with varying decision thresholds. In the case of the Naive Bayes classifier, its AUC performance is typically competitive, especially in well-structured or text-based datasets, although it may fall behind more complex models when dealing with intricate, non-linear relationships.

When compared with Decision Trees and Support Vector Machines, the Naive Bayes classifier stands out for its computational efficiency and ease of implementation. It performs particularly well in scenarios where feature independence assumptions hold approximately true, such as spam detection or document classification. Decision Trees, on the other hand, offer greater flexibility by capturing interactions between features and modeling non-linear patterns. However, they are more prone to overfitting, especially without appropriate pruning or regularization. SVMs generally provide high accuracy and are effective in high-dimensional spaces, but they come with greater computational complexity and require careful tuning of kernel functions and hyperparameters.

The trade-offs observed through this comparative analysis inform the selection of the most suitable model for specific use cases. For example, in real-time applications or environments with limited processing power, Naive Bayes might be preferred due to its simplicity and speed. In contrast, when model interpretability and visualization of decision-making processes are critical, Decision Trees may offer better transparency. SVMs may be selected for more sophisticated tasks that demand high precision in complex, non-linear problem spaces such as image recognition or bioinformatics.

Ultimately, model performance must be evaluated not only by quantitative metrics but also by the practical requirements of the deployment environment. Factors such as training time, interpretability, scalability, and resilience to noisy data all contribute to determining the most appropriate classifier. Additionally, ensemble approaches such as combining Naive Bayes with other models in a voting or stacking ensemble could further enhance prediction accuracy and robustness. By leveraging the strengths of each model, hybrid solutions may offer superior performance compared to any single method alone.

3. Results and Discussion

3.1. Results

The results of this study demonstrate that the Naive Bayes classifier performed exceptionally well in predicting wine quality based on the features provided in the dataset. The model achieved perfect scores across all key performance metrics, including precision, recall, and F1-score, with each metric reaching a value of 1.00 for all three classes: class 1, class 2, and class 3. These results indicate that the model correctly predicted the quality of every wine sample in the dataset without any errors or misclassifications.

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Precision, which measures the proportion of correctly identified positive predictions out of all positive predictions made by the model, was perfect for each class. This suggests that whenever the model classified a wine sample into a specific class, it was always correct. Recall, which assesses the ability of the model to capture all positive instances within a class, also scored 1.00, meaning that the model was able to identify all samples belonging to each respective class without omission. The F1-score, a harmonic mean of precision and recall, being perfect further emphasizes the balance between these two metrics, indicating that the model did not sacrifice precision for recall or vice versa.

The overall accuracy of the Naive Bayes model was also reported as 100%, implying that the model successfully predicted the wine quality for every sample in the dataset without making any errors. This is a significant outcome as achieving perfect accuracy across a multi-class classification problem is uncommon and typically indicates either a highly effective model or an overly simplified dataset.Additionally, the macro average and weighted average metrics both achieved scores of 1.00. The macro average, which computes the average performance across all classes without considering the class distribution, highlights that the model performed uniformly well across all categories. Similarly, the weighted average, which accounts for the number of instances per class when averaging the metrics, also scored perfectly, indicating balanced performance despite the slightly smaller number of samples in class 3 compared to the other two classes.

3.2. Discussion

The perfect results obtained in this study suggest that the Naive Bayes model is highly effective in classifying wine quality within the given dataset. However, achieving a 100% accuracy raises concerns about potential overfitting. Overfitting occurs when a model becomes too closely tailored to the training data, performing exceptionally well on seen data but potentially failing to generalize when exposed to new data.

Several factors could explain the flawless performance observed. First, Naive Bayes works optimally when the dataset meets the assumption of feature independence. If the features in this study are truly independent, it could naturally lead to perfect classification results. Second, the relatively balanced data distribution across the classes (14, 14, and 8 samples) helps prevent bias in the model's learning process, making it easier to identify patterns across all classes equally.

To ensure that the outstanding results are not merely a result of overfitting, further validation is recommended. One effective method would be cross-validation, such as k-fold cross-validation, which splits the data into multiple folds and tests the model on different subsets of data during each iteration. This approach helps assess the model's consistency and robustness more thoroughly.Additionally, it is essential to test the model with a separate validation dataset that was not included during the training phase. Benchmarking the Naive Bayes model against other algorithms, such as Decision Trees, Random Forests, or Support Vector Machines (SVM), can further clarify whether similarly high results can be achieved with different methods. If other models fail to reach perfect scores, it could reinforce the suspicion of overfitting specific to the Naive Bayes model in this dataset.

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Table 1. Predicting Wine Quality Based on Features Using Naive Bayes Classifie

Class	Precision	Recall	F1-Score	Support
1	1.00	1.00	1.00	14
2	1.00	1.00	1.00	14
3	1.00	1.00	1.00	8
Accuracy			1.00	36
Macro avg	1.00	1.00	1.00	36
Weighted avg	1.00	1.00	1.00	36

3.3. Classification Report

The table above presents the evaluation results of a Naive Bayes Classifier used to predict wine quality based on specific features in the dataset. Four evaluation metrics are displayed: Precision, Recall, F1-Score, and Support for three different wine quality classes, along with the overall model accuracy.

3. 3. 1 Precision

1. Precision measures the proportion of correctly predicted positive cases among all positive predictions made by the model. It evaluates how reliable the model's positive predictions are.
2. In the table, a precision score of 1.00 for all three classes means that every prediction made by the model was correct without any false positive cases. Specifically, whenever the model predicted a sample belonged to a certain wine quality class (1, 2, or 3), it was indeed correct.
3. A perfect precision score indicates that the model never misclassified a wine sample as a particular class when it actually belonged to another.

3. 3. 2 Recall

1. Recall (also called sensitivity or true positive rate) measures the ability of the model to identify all relevant positive cases within a class. It assesses how well the model captures all instances of a particular class.
2. The perfect recall score of 1.00 across all classes indicates that the model identified every sample correctly for each class without missing any.
3. A score of 1.00 suggests zero false negatives, meaning no wine samples were overlooked or misclassified into other categories.

3. 3. 3 FI -Score

1. F1-Score is the harmonic mean of precision and recall, offering a balanced measure that accounts for both false positives and false negatives. It is particularly useful when balancing both metrics is important.
2. The F1-Score of 1.00 across all classes indicates a perfect balance between precision and recall.
3. Since both precision and recall are perfect, the F1-Score also achieves perfection, signifying that the model consistently performed well without compromising either metric.

3. 3. 4 Support

4. Support refers to the number of samples present in each class used for evaluation. It provides context to the performance metrics, as small sample sizes can sometimes lead to misleading results.
5. The distribution is relatively balanced, though class 3 has slightly fewer samples compared to the other two classes. The balanced nature of the dataset likely contributed to the model's strong performance, as imbalance can often lead to biased results favoring majority classes.

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3. 3. 5 Accuracy

1. Accuracy measures the proportion of correctly classified samples out of the total number of samples.
2. A perfect accuracy score of 1.00 indicates that the model correctly classified every sample in the dataset.
3. While accuracy is often a primary performance metric, it can be misleading in imbalanced datasets. However, since this dataset is fairly balanced, the perfect accuracy here reinforces the overall success of the model.

3. 3. 6 Macro Averages

1. Macro Average calculates the average of precision, recall, and F1-Score across all classes without considering class sizes.
2. The perfect macro average of 1.00 indicates uniformly high performance across all classes, with no class performing significantly better or worse than others.

3. 3. 7 Weighted Average

1. Weighted Average takes into account the number of samples in each class when averaging precision, recall, and F1-Score.
2. The perfect weighted average of 1.00 indicates that even with slight variations in class sizes, the model maintained consistent performance across the entire dataset.

Table 2. Confusion Matrix

Actual/Class	Predicted 1	Predicted 2	Predicted 3	Total (Support)
Class 1	14	0	0	14
Class 2	0	14	0	14
Class 3	0	0	8	8

3. 4. Confusion Matrix

The confusion matrix presented above summarizes the performance of a classification model applied to a dataset containing three distinct classes. Each row corresponds to the actual (true) class labels, while each column represents the predicted class labels. This matrix is an essential tool for evaluating the performance of a classifier by identifying both correct and incorrect predictions. Here is an in-depth analysis of the matrix:

3.4.3. Structure of the Confusion Matrix

1. Rows (Actual Classes):
    a. Class 1" corresponds to samples that genuinely belong to Class 1
    b. Class 2" corresponds to samples that genuinely belong to Class 2
    c. Class 3" corresponds to samples that genuinely belong to Class 3
2. Columns (Predicted Classes) These represent the labels predicted by the classification model.
3. Diagonal Cells (Correct Predictions) The cells along the diagonal represent the number of samples correctly classified by the model.
4. Off-Diagonal Cells (Misclassifications):

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5. Cells outside the diagonal represent the number of samples that the model misclassified, indicating incorrect predictions.
6. Total (Support):The last column displays the total number of samples for each actual class in the test dataset.

3.4.4. Detailed Breakdown of Results

1. Class 1 (Actual Class):
    a. Correct Predictions (Diagonal Cell): The model correctly classified all 14 samples from Class 1 as "Class 1." This is indicated by the value 14 in the first row, first column.
    2. Misclassifications (Off-Diagonal Cells): There are no misclassifications for Class 1; the values in the first row, second and third columns, are 0. This means no samples from Class 1 were mistakenly predicted as "Class 2" or "Class 3."
    3. Total Support: There are 14 samples in total for Class 1 in the dataset, all of which were correctly classified.
2. Class 2 (Actual Class):
    a. Correct Predictions (Diagonal Cell): The model correctly classified all 14 samples from Class 2 as "Class 2," as indicated by the value 14 in the second row, second column.
    b. Misclassifications (Off-Diagonal Cells): Similar to Class 1, there are no misclassifications for Class 2. The values in the second row, first and third columns, are 0. This indicates that no samples from Class 2 were misclassified as "Class 1" or "Class 3."
    c. Total Support: The total number of samples for Class 2 is 14, and the model classified all of them correctly.
3. Class (Actual Class):
    a. Correct Predictions (Diagonal Cell): The model accurately predicted all 8 samples from Class 3 as "Class 3," as indicated by the value 8 in the third row, third column.
    b. Misclassifications (Off-Diagonal Cells): There are no misclassifications for Class 3; the values in the third row, first and second columns, are 0. This means no samples from Class 3 were incorrectly classified as "Class 1" or "Class 2."
    c. Total Support: The dataset contains 8 samples from Class 3, all of which were correctly classified by the model.

3.4.5. Key Observations):

1. Perfect Classification: The confusion matrix shows perfect classification for all three classes, with no misclassifications. All samples (from Classes 1, 2, and 3) were accurately predicted, as evidenced by the zero values in all off-diagonal cells.
2. This indicates that the model failed to predict all samples from Class 1 and classified them as Class 0.

3.4.4. True Negative (TN):

1. Represents the number of samples that actually belong to Class 1 and were correctly predicted as Class 1.
2. Balanced Dataset:The dataset appears to be relatively balanced, with Class 1 and Class 2 having 14 samples each and Class 3 having 8 samples. While Class 3 has slightly fewer samples, this minor imbalance does not seem to affect the model's performance.
3. High Accuracy Across All Classes:Each class achieved 100% accuracy, meaning the model correctly identified every sample in the test dataset. This is a rare outcome, particularly for real-world datasets, and it indicates that the model performed exceptionally well for this specific dataset.
4. Model Efficiency:The classifier demonstrates its ability to distinguish between the three classes with precision, suggesting that the features in the dataset (e.g., physicochemical attributes) provide strong, non-overlapping signals for classification.

3.4.5 Implications of The Result.

Model Performance:The results suggest that the classification model (likely a Naive Bayes classifier or a similar algorithm) is highly effective for this dataset. The perfect classification might indicate a strong relationship between the dataset's features and the target variable. Dataset

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Characteristics: Thedataset may contain well-separated classes, meaning thephysicochemical attributes (e.g., alcohol content, malic acid, etc.) provide clear distinctions between Classes 1, 2, and 3. Scalability:While the results are highly promising for the test dataset, it is important to assess whether the model generalizes well to new, unseen data. A larger and more diverse dataset should be used to evaluate the model's robustness and prevent overfitting.Practical Applications:In practical settings, this model could be deployed to automate wine classification based on physicochemical features. Such automation would reduce reliance on manual sensory evaluations, improving efficiency and consistency in quality assessment.

4. Conclusion

This study, titled Predicting Wine Quality Based on Features Using Naive Bayes Classifier, provides significant insights into the application of machine learning for wine quality assessment. By leveraging the Naive Bayes classifier, the research successfully demonstrated the feasibility of predicting wine quality based on its physicochemical properties such as pH, alcohol content, acidity levels, sugar concentration, and other related attributes. The findings highlight the capability of this algorithm in handling datasets with multiple correlated features while maintaining simplicity and interpretability.The results of the analysis indicate that the Naive Bayes classifier can achieve high accuracy in categorizing wine quality into predefined classes. The confusion matrix presented in the research shows a perfect classification performance for the given dataset, with all samples accurately assigned to their respective quality categories. This outcome reflects the strong correlation between the physicochemical features of the dataset and the target variable (wine quality), as well as the effectiveness of Naive Bayes in utilizing these features for classification purposes.Furthermore, the study underscores the suitability of Naive Bayes for datasets with clear feature separations and minimal noise.

The classifier's performance suggests that the features used in the dataset were both relevant and discriminative, enabling precise predictions. This emphasizes the importance of feature selection and dataset preprocessing in enhancing the effectiveness of machine learning models in practical applications.However, despite the promising results, there are several considerations for future research. The dataset used in this study appears to be relatively small and well-balanced, which might not fully represent real-world scenarios where data is often larger, more diverse, and imbalanced. To ensure the robustness and generalizability of the model, it is recommended to test the classifier on larger and more complex datasets that include variations in wine types and quality levels. This will help evaluate the algorithm's ability to handle data heterogeneity and potential overfitting.

5. Suggestion

This study highlights the potential of the Naive Bayes classifier in predicting wine quality based on physicochemical features. However, several areas warrant further exploration to improve the robustness, accuracy, and applicability of the methodology. First, future research should focus on expanding the dataset to include larger and more diverse samples, such as wines from different regions, grape varieties, and production techniques. Addressing class imbalances through techniques like oversampling, undersampling, or synthetic data generation can also enhance model performance. Furthermore, incorporating advanced feature engineering methods, such as mutual information, Recursive Feature Elimination (RFE), or LASSO regression, can help identify and prioritize the most relevant features. Additional features, such as sensory evaluation scores, climatic conditions during cultivation, or fermentation processes, could also provide deeper insights into wine quality prediction.

In addition, benchmarking Naive Bayes against advanced machine learning algorithms, such as Random Forest, Gradient Boosting (e.g., XGBoost, LightGBM), Support Vector Machines (SVM), or even deep learning models, could reveal alternative approaches for handling complex datasets. Enhanced model evaluation techniques, such as cross-validation, metrics beyond accuracy (e.g., precision, recall, F1-score, AUC-ROC), and detailed error analysis, should also be implemented to provide a more comprehensive assessment of model performance. Real-world applications could be explored further by integrating predictive models with IoT-enabled devices for real-time data collection, conducting cost-benefit analyses for implementation in wineries, and automating quality control processes to complement or replace traditional sensory evaluations.

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Declaration of Competing Interest

We declare that we have no conflict of interest.

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