

An Analysis Research of White Wine Quality Using Three Machine Learning Models

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Abstract: In today's society, wine has become an indispensable drink on people's tables due to abundant material wealth. Understanding wine quality is crucial in this context. In this work, three popular machine learning models—Support Vector Machine (SVM), Naive Bayes, and Random Forest—are compared through analysis of the white wine dataset. The evaluation metrics employed to assess their performance include precision, recall, and F1 score, providing a comprehensive evaluation of their quality analysis capabilities on white wine data. Results indicate that Random Forest and SVM performed well, achieving satisfactory accuracy and other white wine quality analysis metrics. However, the Naive Bayes model proved unsuitable and could have performed better, underscoring the significance of model selection in machine learning for different datasets and problem domains. This study offers valuable insights into wine quality analysis, emphasizing performance variations among machine learning models. The aforementioned conclusions include noteworthy practical consequences for both the wine business and its clients.

1 INTRODUCTION

In today's society, wine has become integral to people's daily lives, especially in social and celebration events. More and more people are interested in the quality and taste of wine and are eager to enjoy high-quality wine. However, wine quality is affected by many factors, and the complex interactions between these factors make the prediction of wine quality challenging.

The prediction and analysis of wine quality has always been one of the critical tasks for the wine industry and wine lovers. Through in-depth research and analysis of the chemical properties of wine, we can better understand the impact of different factors on wine quality, thereby improving wine production quality and consumer satisfaction.

Traditionally, manually predicting wine grades is a time-consuming and labor-intensive task that requires professional sommeliers and years of experience. However, as technology develops, machine learning and data analysis techniques have become an efficient and accurate method for predicting wine quality. The objective of this project is to investigate and examine the dataset on white wine quality available in the machine learning repository at UCI and in order to

construct an effective model for predicting wine quality. This study will employ various machine learning techniques to determine the most suitable method for solving this problem. First, we will perform an in-depth understanding and data preprocessing of the white wine quality dataset. We will then select, build, train and optimize SVM, Naive Bayes, and Random Forest models. Next, this study will evaluate the model using the same evaluation conditions: accuracy, recall and f1 score.

2 RELATED WORK

Before this study, many scholars had conducted in-depth research on wine quality issues. Z. Dong et al. divided the data set into two parts: one that includes all Bordeaux wine data from 2000 to 2016, and the other that pertains to the famous 1855 Bordeaux wine data set (Dong et al 2020). They used three machine learning models for analysis. In addition, the authors adopted the MLP model, which in addition to standard models, also achieved high accuracy results, which is very suitable for this study (Shaw et al 2019).

Researchers extracted a variety of physical and chemical characteristics and analyzed the impact of

these characteristics on wine quality through correlation, as described in a study (Nandan et al 2023). In a separate study, researchers employed genetic algorithms to develop a comprehensive method for predicting wine quality, classifying it into three levels: high, medium, and low (Chiu et al 2021). Data mining algorithms have also proven effective in analyzing wine quality (Shruthi 2019). Additionally, the issue of uneven sample distribution in the white wine dataset was addressed in a study that utilized SMOTE technology (Hu et al 2016).

Some scholars have tried different models and found that the J48 model also achieved good results in analyzing wine quality (Manisha et al 2021). The relationship between them and wine was revealed by calculating the Pearson correlation coefficient of each variable, as demonstrated in the study by Dahal et al (2021).

3 EXPERIMENTAL METHOD

This experiment will use three models, including SVM, random forest, and naive Bayes, to perform data preprocessing to address the sample imbalance problem in the white wine data set to achieve the experimental goals better.

This investigation utilized three primary machine learning models, namely SVM, Naive Bayes, and Random Forest. This experiment fed white wine quality data into these three models to compare their performance on this dataset, including precision, recall and F1 score. Through this comparison, we can evaluate which machine learning model performs better when dealing with this dataset. In addition to considering a single metric, to obtain a full evaluation of the model's overall performance.

The SVM is a binary classification model. It achieves the prediction of the sample category by introducing a particular plane to divide the data points into two groups. In the SVM algorithm, the critical task is to determine the position and direction of the separation plane so that it can achieve the best division effect between two groups of data points. The basic idea is to map the initial data space to a higher-dimensional feature space employing a non-linear transformation on the fly. In this new space, the aim is to find the optimal linear classification interface. This method introduces an appropriately defined inner product function to achieve this non-linear transformation (Dai and Dong 2020).

The distance between any point and the hyperplane:

$$\gamma = \|w\| |wx + b| \quad (1)$$

The decision boundary:

$$\text{Sign}(wx+b) \quad (2)$$

Naive Bayes methods are derived from the mathematical principle of Bayes' theorem. In fact, Bayes' theorem resembles conditional probability. Its basic idea is to take two random events, A and B, and find the probability that event B will occur given that event A.

$$P(B|A) = \frac{P(A|B) P(B)}{P(A)} \quad (3)$$

The interesting thing about Bayes' theorem is that the probability of B is continuously evaluated when some conditions are known. In the Naive Bayesian approach, we further assume that the features are independent, simplifying the computation. When viewed from a classification perspective, the main goal of Naive Bayes is to establish an efficient mapping that relates new data points to a range of possible classifications in a particular problem domain (Yang 2018).

Random forest is considered as a derivative method of decision tree, and random forest is also an ensemble method. A random forest is basically a forest of multiple smaller decision trees, each of which makes an individualized prediction for a particular data sample. By majority voting these individual prediction values, the maximum value predicted by each tree is obtained as the final overall prediction value (Trivedi and Sehrawat 2018). Usually, the best decision tree is obtained without pruning.

4 EXPERIMENTAL RESULT

In order to make the data have a better representation in different models, so this experiment first preprocessed the wine data. The experiment compares which step is more helpful for the accuracy of the model analysis, normalization processing or standardization under the same model. Normalization was more helpful in predicting the results before presenting the same model. The reason for the greater influence of normalization is that the white wine dataset is sample-uneven in Fig. 1.

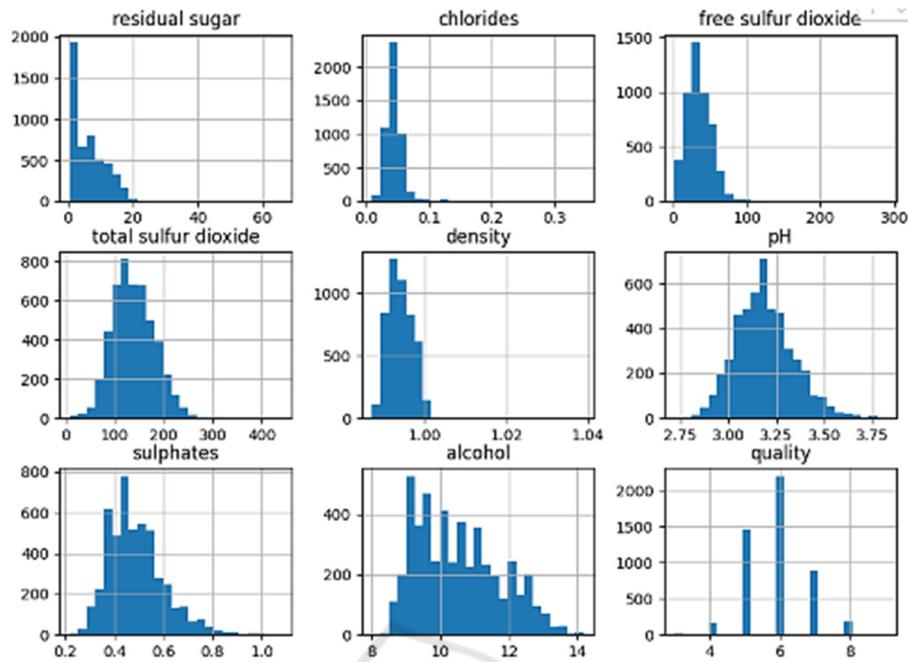


Figure 1: Unbalanced data (Picture credit: Original).

This research extensively examined the dataset's "quality" variable. This column shows 3, 4, 5, 6, 7, 8, and 9 values. Note the lack of 0, 1 and 2 in the initial quality check. In addition, there is another factor to consider. This shows that the dataset has incomplete "quality" values due to data collection or processing restrictions.

categories with less examples. Therefore, while modeling machine learning, the technique to address uneven class distribution must be carefully considered. This is essential to guarantee the model can handle varied inhomogeneities and improve performance and robustness.

So in order to deal with this issue, in this experiment also the data-level techniques primarily address this issue by modifying the distribution of the dataset, achieved through adjusting the sampling of data. This can involve either reducing the number of instances (under-sampling) or increasing the instances (oversampling) (Hu et al 2016).

To enhance the clarity of the link between various features, this study presents the correlation between these attributes in Fig. 3. The utilization of correlation analysis facilitates users in acquiring insights into the aspects that exert the most substantial influence on the quality of white wine. The chart clearly demonstrates that the concentration of alcohol has a substantial influence in potentially influencing the quality of white wine. Fig. 3 demonstrates a significant association between the concentration of alcohol and the quality of white wine. The findings indicate that there is a positive correlation between the alcohol percentage of white wines and their quality scores.

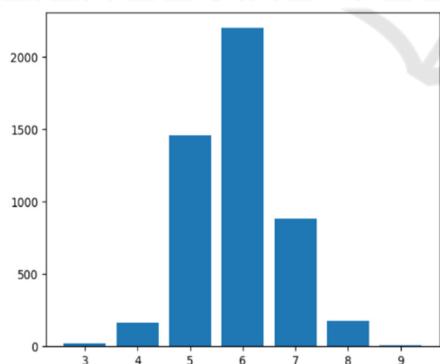


Figure 2: Unbalanced quality data (Picture credit: Original).

Fig. 2 shows that the sample distribution is substantially different from the "quality" values currently available. Some quality levels have many samples, while others have few. Inhomogeneity can affect machine learning modeling by biasing models toward categories with more data and failing on

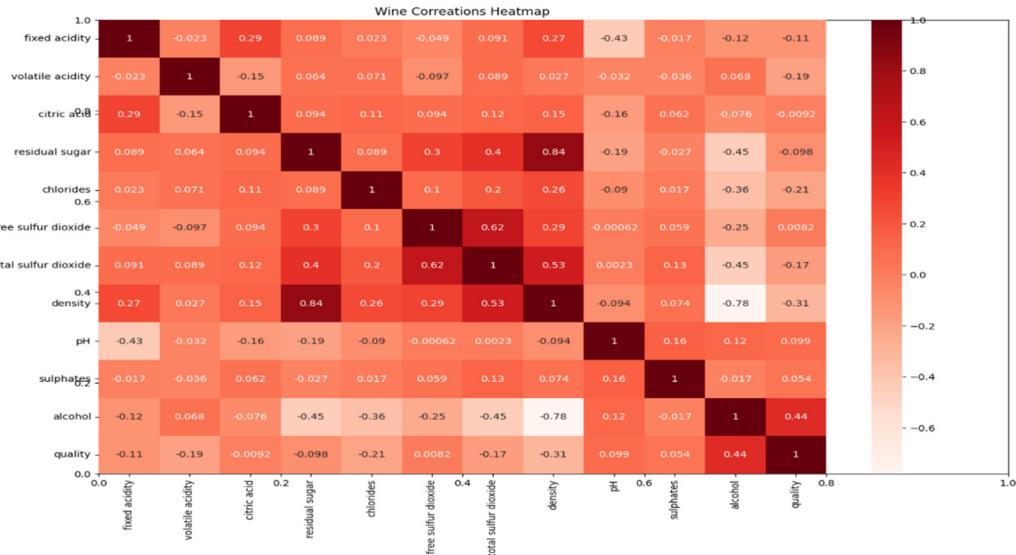


Figure 3: Wine data attributes heatmap (Picture credit: Original).

Balance the sample sizes as much as possible thereby making a stronger connection between the model and the data. The experiment involves partitioning the dataset into two subsets, specifically, the dataset is divided into two subsets, called the training set and the test set, with percentages of 80% and 20% respectively.

This study focuses on analyzing which model will perform well in the white wine dataset by comparing three models: SVM, Simple Bayes and Random Forest. By comparing the accuracy, f1 score, and recall of these three models, it is determined which model is the most suitable for this dataset.

An SVM model represents the instances of a dataset as points in a space, with the objective of creating the widest possible gap to separate instances of different classes. SVM is capable of performing classification for non-linear data as well (Kumar et al 2020). In the SVM model, the initial selection this research made was a linear kernel function. Nevertheless, the results obtained from this experiment were somewhat unsatisfactory, with an accuracy rate of just around 50.5%. Due to the presence of probable non-linearity in the dataset, it was seen that the linear kernel was not appropriate and thus led to suboptimal performance. In order to tackle this issue, we choose to utilize the 'rbf' kernel, since it exhibits a stronger alignment with the fundamental structure of the data. As a result, there was a significant enhancement in accuracy and other performance indicators, with an approximate achievement of 65%. The previous modification highlighted the significance of kernel selection in SVM modelling. The Naive Bayes classifier is less

appropriate for categorizing the quality of wine because of its very low accuracy. The Naive Bayes algorithm can be classified as a white-box classification method due to its characteristic of assigning probabilistic contributions to positive and negative samples for each attribute (Dong et al 2020). The accuracy of the naive bayes is just 41%.

Although use a Gaussian Bayesian model in this research, the final accuracy is still not ideal. The reason should be that the Naive Bayes algorithm often misclassified the data, so it is not suitable for this data set.

The strategic selection of important parameters, namely "criterion," "n_estimators," and "max_depth," plays a crucial role in the Random Forest method. These parameters determine the criteria for data partitioning, the number of trees in the forest, and the depth of each individual tree. The utilization of this particular method serves as a strong preventive measure against overfitting, hence enhancing the model's capacity to generalize. Within the confines of our experimental framework, the decision to establish the number of trees at 300 was the pinnacle of meticulous calibration. The Random Forest algorithm demonstrated exceptional performance, achieving a remarkable accuracy rate of 67% and a significantly better F1 score. These results further underscore the algorithm's superiority when compared to alternative techniques. The results of SVM and random forest have good performance when forecasting the level of white wine, but Naive Bayes is not suitable for classifying these data. Their highest data performance was 67%, and their worst accuracy was 41%

In Fig.4 and Table 1, the experimental results can clearly show the relevant results of each model.

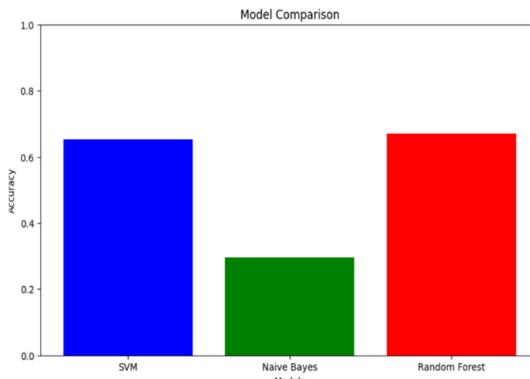


Figure 4: Comparison results of three models (Picture credit: Original).

Table 1: Results display of three models.

	Accuracy	Recall	F1 score
SVM	0.65	0.65	0.64
Naive Bayes	0.41	0.29	0.27
Random Forest	0.67	0.67	0.67

5 CONCLUSION

This study aims to analyze the white wine dataset and compare the performance of three models: SVM, Naive Bayes, and Random Forest on this dataset. Determine which model best fits the dataset by comparing the accuracy, F1 score, and recall of the three models. With an accuracy of almost 67% and other index values. The researchers determined that the random forest model exhibited superior performance. The SVM model has a little inferior level of accuracy compared to the random forest model, but it also shows excellent analytical and predictive capabilities in the white wine data set. Considering the possibility that the data may not be linear and the linear kernel function results in suboptimal accuracy, this research tried to change the kernel function to a Gaussian kernel function, which fits the data form better. Hence, the accuracy and other results were about 65%. The worst-performing model is the Naive Bayes model. After multiple optimizations of this model, its accuracy is only 41%. The reason for this result is that the uneven sample distribution of the data set affects the model's accuracy. Since the Naive Bayes method is a white-

box classification method and often needs to be more accurate for this dataset.

This study fills a research gap regarding white wine data and the fit between the three models we employed. This study gives readers a deeper understanding of the correlation between accuracy across datasets and different models.

Due to the author's limited academic level and insufficient optimization capabilities for models such as Naive Bayes, the expressiveness of the model has yet to reach a high level. In the future, the author will continue to delve into machine learning and learn algorithms for optimizing machine models. Improve technical level.

REFERENCES

- Z. Dong, X. Guo, S. Rajana, and B. Chen, "Understanding 21st Century Bordeaux Wines from Wine Reviews Using Naïve Bayes Classifier," *Beverages*, 2020, pp. 5
- B. Shaw, A. K. Suman, and B. Chakraborty, "Wine Quality Analysis Using Machine Learning, Emerging Technology in Modelling and Graphics", *Emerging Technology in Modelling and Graphics*, 2019.
- M. Nandan, H. Raj Gupta and M. Mondal, "Building a Classification Model based on Feature Engineering for the Prediction of Wine Quality by Employing Supervised Machine Learning and Ensemble Learning Techniques," *International Conference on Computer, Electrical & Communication Engineering (ICCECE)*, 2023, pp. 1-7.
- T. H. -Y. Chiu, C. Wu, and C. -H. Chen, "A Generalized Wine Quality Prediction Framework by Evolutionary Algorithms," *International Journal of Interactive Multimedia and Artificial Intelligence*, 2021, p. 60.
- P. Shruthi, "Wine Quality Prediction Using Data Mining," *Environment, Computing & Communication Engineering (ICATIECE)*, 2019, pp. 23-26.
- G. Hu, T. Xi, F. Mohammed and H. Miao, "Classification of wine quality with imbalanced data," *IEEE International Conference on Industrial Technology*, 2016, pp. 1712-1217.
- K. Manisha, P. Richa, J. Mayurika and K. Manish, "Analysis of white wine using machine learning algorithms," *Materials Today: Proceedings*, 2021, pp. 11087-11093.
- K. R. Dahal, J.N. Dahal, H. Banjade, S. Gaire, "Prediction of Wine Quality Using Machine Learning Algorithms," *Open Journal of Statistics*, 2021, pp. 278-289.
- T. -T. Dai and Y. -S. Dong, "Introduction of SVM Related Theory and Its Application Research," *3rd International Conference on Advanced Electronic Materials*, 2020, pp. 230-233.
- F. -J. Yang, "An Implementation of Naive Bayes Classifier," *International Conference on Computational Science and Computational Intelligence (CSCI)*, 2018, pp. 301-306.

- A. Trivedi and R. Sehrawat, "Wine Quality Detection through Machine Learning Algorithms," *International Conf. on Recent Innovations in Electrical, Electronics & Communication Engineering* (ICRIECE), 2018, pp. 1756-1760.
- S. Kumar, K. Agrawal and N. Mandan, "Red Wine Quality Prediction Using Machine Learning Techniques," *International Conf. on Computer Communication and Informatics* (ICCCI), 2020, pp. 1-6.

