Master Degree Project

UNIVERSITY
OF SKÖVDE

WINE QUALITY PREDICTION MODEL USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

The quality of a wine is important for the consumers as well as the wine industry. The traditional (expert) way of measuring wine quality is time-consuming. Nowadays, machine learning models are important tools to replace human tasks. In this case, there are several features to predict the wine quality but the entire features will not be relevant for better prediction. So, our thesis work is focusing on what wine features are important to get the promising result. For the purpose of classification model and evaluation of the relevant features, we used three algorithms namely support vector machine (SVM), naïve Bayes (NB), and artificial neural network (ANN). In this study, we used two wine quality datasets red wine and white wine. To evaluate the feature importance we used the Pearson coefficient correlation and performance measurement matrices such as accuracy, recall, precision, and f1 score for comparison of the machine learning algorithm. A grid search algorithm was applied to improve the model accuracy. Finally, we achieved the artificial neural network (ANN) algorithm has better prediction results than the Support Vector Machine (SVM) algorithm and the Naïve Bayes (NB) algorithm for both red wine and white wine datasets.

Keywords— Classification, Support Vector Machine, Naïve Bayes, Artificial Neural Network.

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1. Introduction

The quality of the wine is a very important part for the consumers as well as the manufacturing industries. Industries are increasing their sales using product quality certification. Nowadays, all over the world wine is a regularly used beverage and the industries are using the certification of product quality to increases their value in the market. Previously, testing of product quality will be done at the end of the production, this is time taking process and it requires a lot of resources such as the need for various human experts for the assessment of product quality which makes this process very expensive. Every human has their own opinion about the test, so identifying the quality of the wine based on humans experts it is a challenging task.

There are several features to predict the wine quality but the entire features will not be relevant for better prediction.

The research aims to what wine features are important to get the promising result by implementing the machine learning classification algorithms such as Support Vector Machine (SVM), Naïve Bayes (NB), and Artificial Neural Network (ANN), using the wine quality dataset.

The wine quality dataset is publically available on the UCI machine learning repository (Cortez et al., 2009). The dataset has two files red wine and white wine variants of the Portuguese “Vinho Verde” wine. It contains a large collection of datasets that have been used for the machine learning community. The red wine dataset contains 1599 instances and the white wine dataset contains 4898 instances. Both files contain 11 input features and 1 output feature. Input features are based on the physicochemical tests and output variable based on sensory data is scaled in 11 quality classes from 0 to 10 (0-very bad to 10-very good).

Feature selection is the popular data preprocessing step for generally (Wolf and Shashua, 2005). To build the model it selects the subset of relevant features. According to the weighted of the relevance of the features, and with relatively low weighting features will be removed. This process will simplify the model and reduce the training time, and increase the performance of the model (Panday et al., 2018). We pay attention to feature selection is also the study direction. To evaluate our model, accuracy, precision, recall, and f1 score are good indicators to evaluate the performance of the model.

The report is divided into 7 sections, including this one. In Section 2 we discuss the background and related work. In Section 3 we formulate our research question and hypothesis. Section 4 describes the methodologies. Section 5 discusses the experimental design. In Section 6 results and discussion of the whole work. In Section 7 we discuss the conclusions and future work.

2. Background

A wide range of machine learning algorithms is available for the learning process. This section describes the classification algorithms used in wine quality prediction and related work.

2.1. Classification algorithm

2.1.1. Support Vector Machine

The support vector machine (SVM) is the most popular and most widely used machine learning algorithm. It is a supervised learning model that can perform classification and regression tasks. However, it is primarily used for classification problems in machine learning (Gandhi, 2018).

The SVM algorithm aims to create the best line or decision boundary that can separate n-dimensional space into classes. So we can put the new data points easily in the correct groups. This best decision boundary is called a hyperplane.

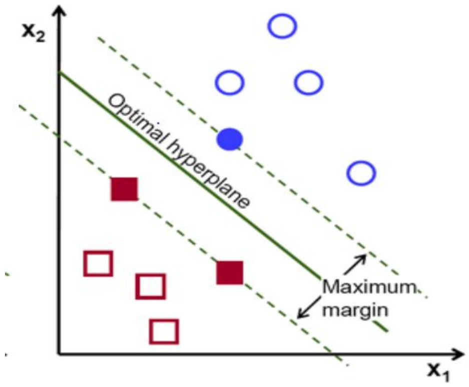


Figure 1: Support Vector Machine (Gandhi, 2018)

The support vector machine selects the extreme data points that helping to create the hyperplane. In Figure 1, two different groups are classified by using the decision boundary or hyperplane:

The SVM model is used for both non-linear and linear data. It uses a nonlinear mapping to convert the main preparing information into a higher measurement. The model searches for the linear optimum splitting hyperplane in this new measurement. A hyperplane can split the data into two classes with an appropriate nonlinear mapping to suitably high measurements and for the finding, this hyperplane SVM uses the support vectors and edges (J. Han et al., 2012). The SVM model is a representation of the models as a point in space, the different classes are isolated by the gap to mapped with the aim that instances are wide as would be careful. The model can perform out a nonlinear form of classification (Kumar et al., 2020).

2.1.2. Naive Bayesian

The naive Bayesian is the simple supervised machine learning classification algorithm based on the Bayes theorem. The algorithm assumes that the feature conditions are independent of the given class (Rish, 2001). The naive Bayes algorithm helps to build fast machine learning models that can make a fast prediction. The algorithm finds whether a particular portion has a spot by a particular class it utilizes the probability of likelihood (Kumar et al., 2020).

2.1.3. Artificial Neural Network

The artificial neural network is a collection of neurons that can process information. It has been successfully applied to the classification task in several industries, including the commercial, industrial, and scientific filed (Zhang, 2000). The algorithm model is a connection between the neurons that are interconnected with the input layer, a hidden layer, and an output layer (Hewahi, 2017).

The neural network is constant because while an element of the neural network is failing, it can continue its parallel nature without any difficulties (Mhatre et al., 2015).

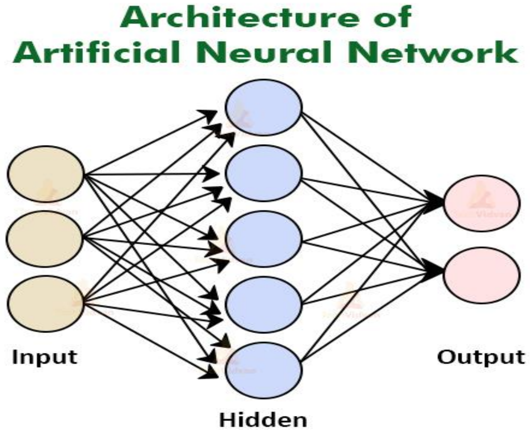


Figure 2: Artificial Neural Network (says, 2020)

The implementation of the artificial neural network consists of three layers: input, hidden, and, output as shown in Figure 2. The function at the input layer is mapped the input attribute which passes input to the hidden layer. The hidden layer is a middle layer where all input with the weights is received to each node in the hidden layer. The output layer is mapped to the predicted elements (says, 2020).

The connection among the neurons is called weights, it has numerical values and this weight among the neurons are determining the learning ability of the neural network. The activation function is used to standardize the output from the neurons and these activation functions are evaluate the output of the neural network in the mathematical equations. Each neuron has an activation function. The neural network is hard to understand without mathematical reasoning. Activation functions are also called the transmission function and also helps to standardize the output range between -1 to 1 or 0 to 1.

2.2. Related Work

Kumar et al. (2020) have used prediction of red wine quality using its various attributes and for the prediction, they used random forest, support vector machine, and naive Bayes techniques (Kumar et al., 2020). They have calculated the performance measurement such as precision, recall, f1-score, accuracy, specificity, and misclassification error. Among these three techniques, they achieved the best result from the support vector machine as compare to the random forest and naive Bayes techniques. They achieved the accuracy of the support vector machine technique is 67.25%.

Gupta, (2018) has used important features from red wine and white wine quality using various machine learning algorithms such as linear regression, neural network, and support vector machine techniques. They used two ways to determine the wine quality. Firstly the dependency of the target variable on the independent variable and secondly predicting the value of the target variable and conclusion that all features are not necessary for the prediction instead of selecting only necessary features to predict the wine quality (Gupta, 2018).

Dahal et al., (2021) has predicted the wine quality based on the various parameters by applying various machine learning models such as rigid regression, support vector machine, gradient boosting regressor, and multi-layer artificial neural network. They compare the performance of the models to predict wine quality and from their analysis, they found gradient boosting regressor is the best model to other model performances with the MSE, R, and MAPE of 0.3741, 0.6057, and 0.0873 respectively(Dahal et al., 2021).

Er, and Atasoy, (2016) has proposed the method to classify the quality of the red wine and white wine using three machine learning algorithm such as k-nearest-neighborhood, random forest, and support vector machine. They used principal component analysis for the feature selection and they have achieved the best result using the random forest algorithm (Er, 2016).

Lee et al., (2015) has proposed a method decision tree-based to predict the wine quality and compare their approach using three machine learning algorithm such as support vector machine, multi-layer perceptron, and BayesNet. They found their proposed method is better compared to other stated methods (Lee et al., 2015).

P. Appalasamy et al., (2012) have predicted the wine quality based on the physiochemical data. They used both red wine and white wine datasets and applied the decision tree and naive Bayes algorithms. They compare the results of these two algorithms and conclude that the classification approach can help to improve the wine quality during production (P. Appalasamy et al., 2012).

3. Problem

3.1. Problem Definition

Based on the articles reported in section 2.2, the significance of each feature for the wine quality prediction is not yet quantified. And in terms of performance, the current accuracy is about 67.25%. Thus, in this thesis, we considered two aspects of the problems mentioned above. The first one is the study of the importance of the features for the prediction of wine quality. The secondly, performance of the prediction model can be improved using a neural network with other ordinary classifiers used by the articles cited above.

3.2. Research Aim

The following research question and hypothesis are formulated.

1. What wine features are important to get a promising result?

The researchers have used a neural network for the regression task but for the classification task neural network was never used. Hypothetically, the current prediction model that has been obtained by researchers will be improved by using the neural network.

To address the research question the following objectives are formulated :

- To balance the dataset.
- To analyze the impact of the features.
- To optimize the classification models through hyperparameter tuning.
- To model and evaluate the approaches.

4. Method and Approach

4.1. Data Description

The red wine and white wine datasets have been used in this paper which is obtained from the UCI machine learning repository it contains a large collection of datasets that have been used for the machine learning community. The dataset contains two excel files, related to red wine and white wine variants of the Portuguese "Vinho Verde" wine (Cortez et al., 2009). The red wine dataset contains 1599 instances and the white wine dataset contains 4898 instances. Both datasets have 11 input variables (based on physicochemical tests): fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulfates, alcohol, and 1 output variable (based on sensory data): quality. Sensory data is scaled in 11 quality classes from 0 to 10 (0-very bad to 10-very good). Below Table 1 description of the attributes.

Table 1: Attribute description

Attributes	Description
fixed acidity	Fixed acids, numeric from 3.8 to 15.9
volatile acidity	Volatile acids, numeric from 0.1 to 1.6
citric acid	Citric acids, numeric from 0.0 to 1.7
residual sugar	residual sugar, numeric from 0.6 to 65.8
chlorides	Chloride, numeric from 0.01 to 0.61
free sulfur dioxide	Free sulfur dioxide, numeric: from 1 to 289
total sulfur dioxide	Total sulfur dioxide, numeric: from 6 to 440
density	Density, numeric: from 0.987 to 1.039
pH	pH, numeric: from 2.7 to 4.0
sulfates	Sulfates, numeric: from 0.2 to 2.0
alcohol	Alcohol, numeric: from 8.0 to 14.9
quality	Quality, numeric: from 0 to 10, the output target

4.2. Feature selection

Feature selection is the method of selection of the best subset of features that will be used for classification (Fauzi et al., 2017). Most of the feature selection method is divided into a filter and wrapper, the filter uses the public features work individually from the learning algorithm and the wrapper evaluates the features and chooses attributes based on the estimation of the accuracy by using a search algorithm and specific learning model (Onan and Korukoğlu, 2017).

In this study, for a better understanding of the features and to examines the correlation between the features. The Pearson correlation coefficient is calculated for each feature in Table 1, this shows the pairwise person correlation coefficient P, which is calculated by using the below formula (Dastmard, 2013).

$$P_{x,y} = \frac{\mathrm{cov}\ (\mathrm{X}, \mathrm{Y})}{\sigma X, \mathrm{\sigma Y}}$$

Where the σ is the standard deviation of the features X and Y and cov is the covariance. The range of the correlation coefficient from -1 to 1. Point 1 value implies linear equation is describes the correlation between X and Y strong positive, which is all data points are lying on a line for Y increases as X increases. Where point -1 value indicates that strong negative correlations between data points. All data points lie on a line in which Y decreases as X increases. And point 0 indicates that there is an absence of correlation between the points (Dastmard, 2013).

4.3. HyperParametr tuning

The grid search is a basic method for hyperparameter tuning. Perform an inclusive search on the hyperparameter set specified by the user. Grid search is suitable for several hyperparameters with limited search space. The grid search algorithm is straightforward with enough resources, the most accurate prediction can be drawn and users can always find the best combination (Joseph, 2018). Running grid search in parallel is easy because each test is run separately without affected by the time series. The results of one experiment are independent of the results of other experiments. Computing resources can be allotted in a very flexible way. In addition, grid search can accept a limited sampling range, because too many settings are not suitable. In practice, grid search is almost preferable only when the user has enough knowledge with these hyperparameters to allow the definition of a narrow search space, and it is not necessary to adjust more than three hyperparameters simultaneously. Although other search algorithms may have more useful features, grid search is still the most widely used method due to its mathematical simplicity (Yu and Zhu, 2020).

4.4. Evaluation

The performance measurement is calculated and evaluate the techniques to detect the effectiveness and efficiency of the model. There are four ways to check the predictions are correct or incorrect:

- True Positive: Number of samples that are predicted to be positive which are truly positive.
- False Positive: Number of samples that are predicted to be positive which are truly negative.
- False Negative: Number of samples that are predicted to be negative which are truly positive.
- True Negative: Number of samples that are predicted to be negative which are truly negative.

Below listed techniques, we use for the evaluation of the model.

1. Accuracy – Accuracy is defined as the ratio of correctly predicted observation to the total observation. The accuracy can be calculated easily by dividing the number of correct predictions by the total number of predictions.

$$\text{Accuracy } = \frac{\text{True Positive } + \text{ True Negative}}{\text{True Positive} + \text{False Positive} + \text{ False Negative } + \text{ True Negative}}$$

2. Precision – Precision is defined as the ratio of correctly predicted positive observations to the total predicted positive observations.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

3. Recall – Recall is defined as the ratio of correctly predicted positive observations to all observations in the actual class. The recall is also known as the True Positive rate calculated as,

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

4. F1 Score – F1 score is the weighted average of precision and recall. The f1 score is used to measure the test accuracy of the model. F1 score is calculated by multiplying the recall and precision is divided by the recall and precision, and the result is calculated by multiplying two.

$$\text{F1 score } = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

Accuracy is the most widely used evaluation metric for most traditional applications. But the accuracy rate is not suitable for evaluating imbalanced data sets, because many experts have observed that for extremely skewed class distributions, the recall rate for minority classes is typically 0, which means that no classification rules are generated for the minority class. Using the terminology in information retrieval, the precision and recall of the minority categories are much lower than the majority class. Accuracy gives more weight to the majority class than to the minority class, this makes it challenging for the classifier to implement well in the minority class.

For this purpose, additional metrics are coming into widespread usage (Guo et al., 2008).

The F1 score is the popular evaluation matric for the imbalanced class problem (Estabrooks and Japkowicz, 2001). F1 score combines two matrices: precision and recall. Precision state how accurate the model was predicting a certain class and recall state that the opposite of the regrate misplaced instances which are misclassified. Since the multiple classes have multiple F1 scores. By using the unweighted mean of the F1 scores for our final scoring. We want our models to get optimized to classify instances that belong to the minority side, such as wine quality of 3, 8, or 9 equally well with the rest of the qualities that are represented in a larger number.

5. Experimental design

5.1. Unbalanced Data

Visualize the quality class label in the red wine and white wine dataset as follows:

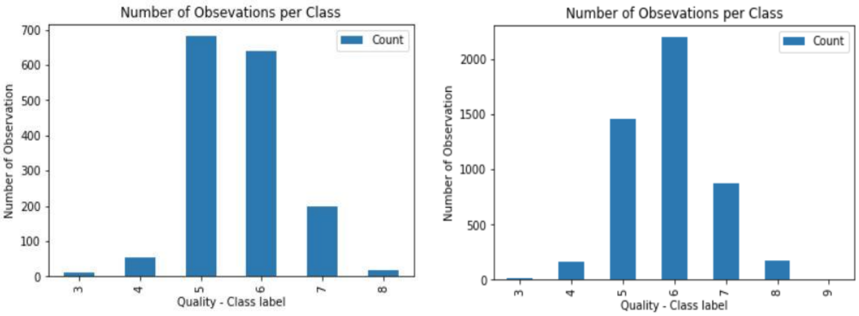


Figure 3: Distribution of Red & White wine quality

Figure 3 shows that the quality class of the red wine and white wine dataset shows that its distribution and we can see the most value is 5 in red wine and 6 in white wine, and all class values are in between 3 to 8 in red wine and 3 to 9 in white wine.

The datasets are the imbalanced distribution of red wine and white wine where the separate classes are not equally represented. This imbalanced data can lead to overfitting and underfitting algorithms. The red wine's highest quality class 5 instances are 681 and white wine highest quality class 6 instances are 2198. Both datasets are unbalanced with the number of instances ranging from 5 in the minority class up to 681 in red wine and ranging from 6 in the minority class up to 2198 in the majority class. The highest quality scores are rarely paralleled to the middle classes. By using resampling this problem can be solved, the resampling is by adding copies of examples from the under-represented class of unnaturally creating such instances (over-sampling) or either by removing from the over-represented class (under-sampling). Mostly, it will be better to over-sample unless you have sufficiently of data. However, there are some disadvantages to over-sampling it increases the instances of the dataset, so the processing time is increasing to build the model. Over-sampling can lead to overfitting when putting the extremes (Drummond and Holte, 2003). Therefore the resampling is preferred.

A good way to deal with the imbalanced datasets by applying the supervised synthetic minority oversampling technique (SMOTE) filter (Chawla, 2005). SMOTE is an over-sampling technique in which a lesser amount of classes in the training set is over-sampled and creating the new sample form to relieve the class imbalance. Therefore, to solve the data imbalanced problem we used the SMOTE technique.

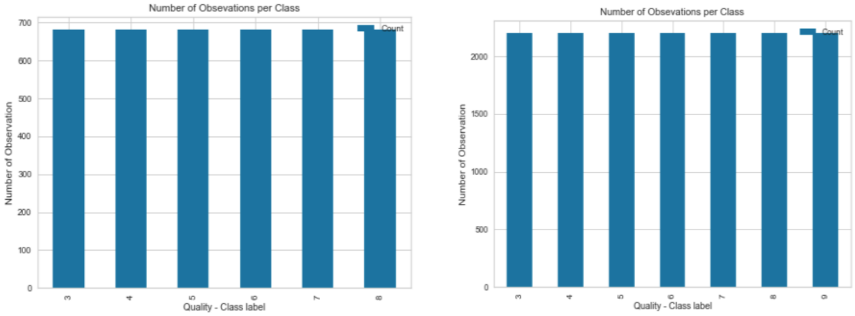
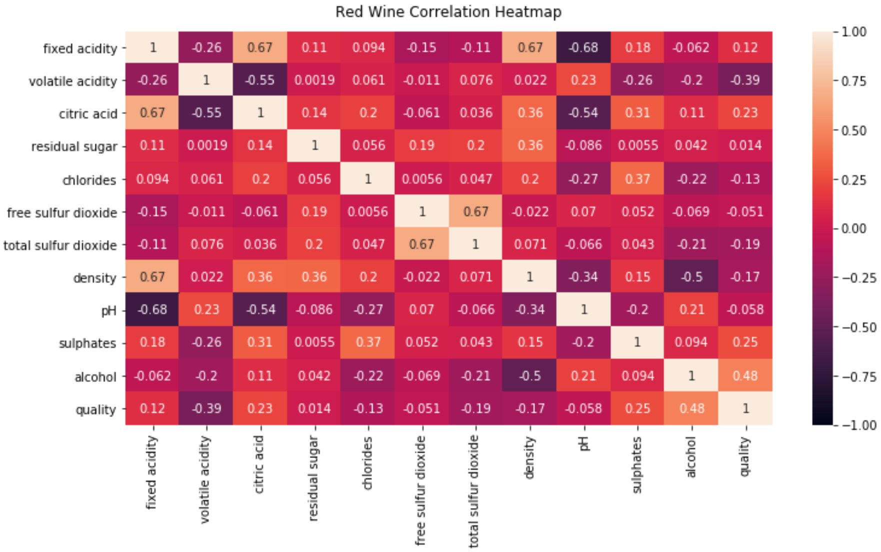


Figure 4: Effect of balancing dataset

After applying the SMOTE technique to balance the dataset as shown in Figure 4, the default and non-default amount of instances are the same, that is 681 instances in the red wine and 2198 instances in the white wine.

5.2. Feature Selection

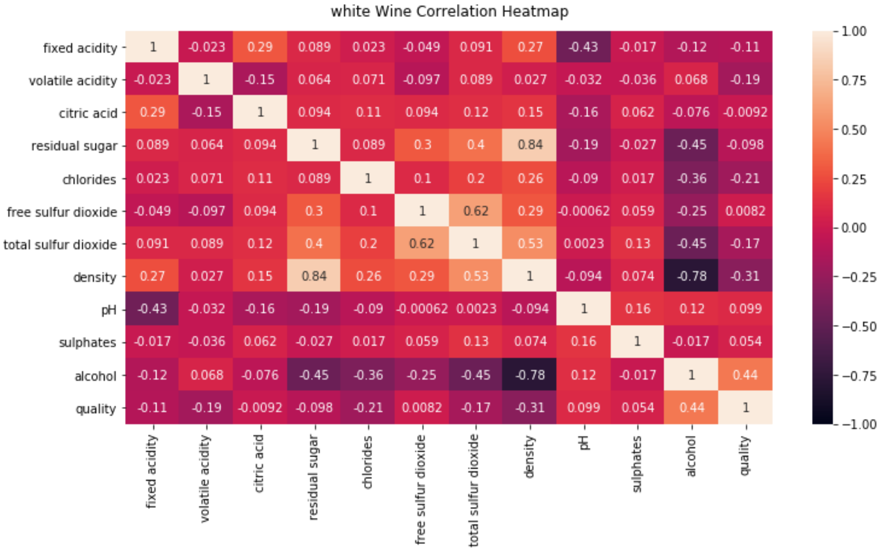
For a better understanding of the features and to examines the correlation between the features. We use the Pearson coefficient correlation matrices to calculate the correlation between the features.



	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1	-0.26	0.67	0.11	0.094	-0.15	-0.11	0.67	-0.68	0.18	-0.062	0.12
volatile acidity	-0.26	1	-0.55	0.0019	0.061	-0.011	0.076	0.022	0.23	-0.26	-0.2	-0.39
citric acid	0.67	-0.55	1	0.14	0.2	-0.061	0.036	0.36	-0.54	0.31	0.11	0.23
residual sugar	0.11	0.0019	0.14	1	0.056	0.19	0.2	0.36	-0.086	0.0055	0.042	0.014
chlorides	0.094	0.061	0.2	0.056	1	0.0056	0.047	0.2	-0.27	0.37	-0.22	-0.13
free sulfur dioxide	-0.15	-0.011	-0.061	0.19	0.0056	1	0.67	-0.022	0.07	0.052	-0.069	-0.051
total sulfur dioxide	-0.11	0.076	0.036	0.2	0.047	0.67	1	0.071	-0.066	0.043	-0.21	-0.19
density	0.67	0.022	0.36	0.36	0.2	-0.022	0.071	1	-0.34	0.15	-0.5	-0.17
pH	-0.68	0.23	-0.54	-0.086	-0.27	0.07	-0.066	-0.34	1	-0.2	0.21	-0.058
sulphates	0.18	-0.26	0.31	0.0055	0.37	0.052	0.043	0.15	-0.2	1	0.094	0.25
alcohol	-0.062	-0.2	0.11	0.042	-0.22	-0.069	-0.21	-0.5	0.21	0.094	1	0.48
quality	0.12	-0.39	0.23	0.014	-0.13	-0.051	-0.19	-0.17	-0.058	0.25	0.48	1

Figure 5: correlation matrices red wine

From Figure 5 red wine correlation matrix we ranked the features according to the high correlation values to the quality class such as freatures are 'alcohol', 'volatile acidity', 'sulphates', 'citric acid', 'total sulfur dioxide', 'density', 'chlorides', 'fixed acidity', 'pH', 'free sulfur dioxide', 'residual sugar'.



	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1	-0.023	0.29	0.089	0.023	-0.049	0.091	0.27	-0.43	-0.017	-0.12	-0.11
volatile acidity	-0.023	1	-0.15	0.064	0.071	-0.097	0.089	0.027	-0.032	-0.036	0.068	-0.19
citric acid	0.29	-0.15	1	0.094	0.11	0.094	0.12	0.15	-0.16	0.062	-0.076	-0.0092
residual sugar	0.089	0.064	0.094	1	0.089	0.3	0.4	0.84	-0.19	-0.027	-0.45	-0.098
chlorides	0.023	0.071	0.11	0.089	1	0.1	0.2	0.26	-0.09	0.017	-0.36	-0.21
free sulfur dioxide	-0.049	-0.097	0.094	0.3	0.1	1	0.62	0.29	-0.00062	0.059	-0.25	0.0082
total sulfur dioxide	0.091	0.089	0.12	0.4	0.2	0.62	1	0.53	0.0023	0.13	-0.45	-0.17
density	0.27	0.027	0.15	0.84	0.26	0.29	0.53	1	-0.094	0.074	-0.78	-0.31
pH	-0.43	-0.032	-0.16	-0.19	-0.09	-0.00062	0.0023	-0.094	1	0.16	0.12	0.099
sulphates	-0.017	-0.036	0.062	-0.027	0.017	0.059	0.13	0.074	0.16	1	-0.017	0.054
alcohol	-0.12	0.068	-0.076	-0.45	-0.36	-0.25	-0.45	-0.78	0.12	-0.017	1	0.44
quality	-0.11	-0.19	-0.0092	-0.098	-0.21	0.0082	-0.17	-0.31	0.099	0.054	0.44	1

Figure 6: correlation matrices white wine

Similarily, from Figure 6 white wine correlation matrix we ranked the features according to the high correlation values to the quality class such as freatures are 'alcohol', 'density', 'chlorides', 'volatile acidity', 'total sulfur dioxide', 'fixed acidity', 'pH', 'residual sugar', 'sulphates', 'citric acid', 'free sulfur dioxide'.

5.3. Data Standardization

Scikit-learn is a python module, it integrates the newest machine learning algorithm for supervised and unsupervised problems (Pedregosa et al., 2011).

The data standardization technique can scale the features among 0 and 1, it will be useful for learning the model, by applying it to all the numeric features and then separating data by standard derivation (Pedregosa et al., 2011). So, we use this technique to standardize the data.

The formula of standardization is :

$$z_i = \frac{xi - u}{\sigma}$$

σ is the standard derivation, xi is each value, and u is the mean value of the array x.

5.4. Data Separation

The scikit-learn library is splitting the data into a training and testing set. So we split the dataset test size is equal to 0.2. The train test split method randomly splits the sample data into the testing set and the training set, so this will avoid the unseen division of the sample data.

5.5. HyperParameter tuning

To improve the performance of the support vector machine model we used hyperparameters, the number of observations, and the outcome of each observation, mentioned below in Table 2.

Table 2: Hyperparameter tuning for SVM Model

Parameter	Observations	Red wine outcome	White wine outcome
C	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 10	3	5
kernel	‘linear, ‘rbf’, ‘sigmoid’	‘rbf’	‘rbf’
gamma	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 10	0.4	2.2

Similarly, to improve the performance of the artificial neural network model we used hyperparameters, the number of observations, and the outcome of each observation, mentioned below Table 3.

Table 3: Hyperparameter tuning for ANN Model

Parameter	Observations	Red wine outcome	White wine outcome
hiden_layer_sizes	[100, 50], [200, 100], [300, 200], [400, 200]	[200, 100]	[400, 200]
activation	‘tanh’, ‘relu’, ‘logistic’	‘tanh’	‘tanh’
solver	‘lbfgs’, ‘adam’, ‘sgd’	‘adam’	‘adam’
Max_iter	200, 300, 400, 500, 700, 1000	300	400
random_ state	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10	4	6
learning_ rate_init	0.001, 0.002, 0.003, …., 0.01	0.006	0.006

5.6. Model and Evaluation

For the implementation of the model, we used machine learning algorithms such as support vector machine (SVM), naïve Bayes (NB), and artificial neural network (ANN). To adobe algorithms, we use the scikit-learn python machine learning libraries (scikit-learn, 2021).

The evaluation results were achieved from each implementation of the classification algorithm calculated. As mentioned in the Evaluation sub-section.

6. Results and Discussions

6.1. Feature Selection result

To evaluate the performance of each feature, a Pearson correlation coefficient technique was implemented and obtained results. Above red wine Figure 5, and white wine Figure 6 shows the importance of each feature and according to the high relationship with the quality, the features were ranked.

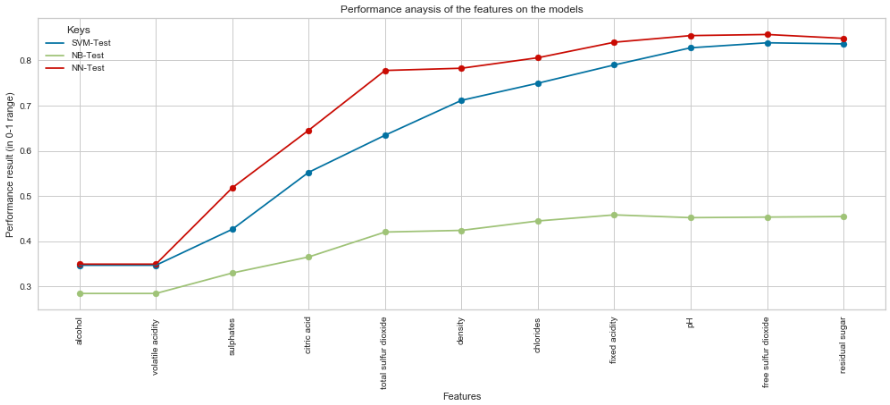


Figure 7: Red wine performance analysis of the feature model

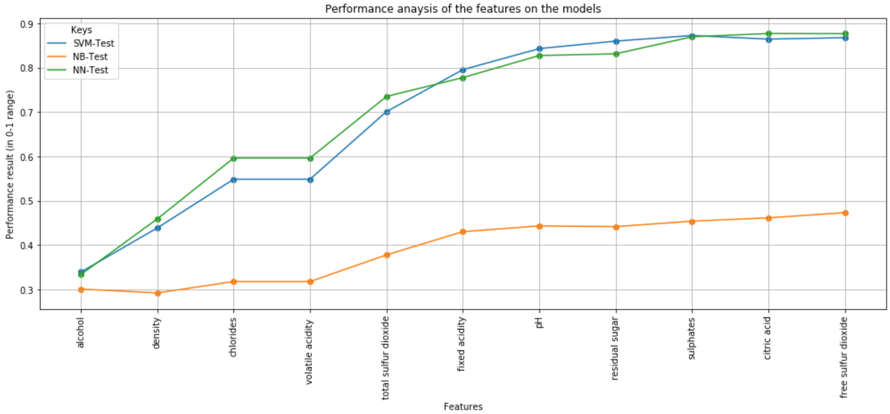


Figure 8: white wine performance analysis of the feature model

Therefore, the analysis of groups of features from left to right is implemented, shown in Figure 7 and Figure 8 from both datasets first

10 features are selected and the last feature is excluded because there is no improvement and it is decreasing the performance of the model. 'residual sugar' feature from red wine datasets and 'free sulfur dioxide' feature from the white wine dataset is excluded for the final implementation of the models. The above red wine performance analysis Figure 7 and white wine performance analysis Figure 8 show a clue that the prediction models achieved better results with their selected 10 features.

6.2. Model Results

The importance of the features are identified and from both dataset's first 10 features were selected and the last feature was excluded, above red wine performance analysis Figure 7 and white wine performance analysis Figure 8 shows that the performance in terms of accuracy.

Firstly, these selected features were implemented on the unbalanced classes, Figure 3 shows the unbalanced classes and the performance of the prediction model, in terms of accuracy, precision, recall, and F1 score is examined, as expressed in Table 4 red wine and Table 5 white wine.

Table 4: Red wine Unbalanced class performance.

	SVM			NB			ANN		
Class	Precision	Recall	F1 score	Precision	Recall	F1 score	Precision	Recall	F1 score
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.17	0.50	0.26	0.00	0.00	0.00
5	0.79	0.79	0.79	0.73	0.60	0.66	0.70	0.82	0.76
6	0.60	0.60	0.60	0.54	0.53	0.54	0.57	0.62	0.59
7	0.62	0.62	0.62	0.32	0.43	0.37	0.62	0.23	0.33
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Accuracy	69.06			54.06			64.37		

Table 5: White wine unbalanced class performance.

	SVM			NB			ANN		
Class	Precision	Recall	F1 score	Precision	Recall	F1 score	Precision	Recall	F1 score
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.53	0.21	0.30	0.31	0.28	0.30	0.36	0.10	0.16
5	0.72	0.65	0.68	0.53	0.58	0.55	0.56	0.54	0.55
6	0.66	0.81	0.72	0.54	0.36	0.43	0.55	0.66	0.60
7	0.68	0.54	0.60	0.33	0.66	0.44	0.39	0.34	0.36
8	0.86	0.40	0.54	0.17	0.02	0.04	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Accuracy	67.83			45.55			52.65		

Then these selected features were implemented on the balanced class, Figure 4 shows that the balancing of each class and the performance of the prediction model, in terms of accuracy, precision, recall, and f1 score is examined, as expressed in Table 6 red wine and Table 7 white wine.

Table 6: Red wine balanced class performance.

	SVM			NB			ANN		
Class	Precision	Recall	F1 score	Precision	Recall	F1 score	Precision	Recall	F1 score
3	1.00	1.00	1.00	0.53	0.80	0.63	0.99	1.00	1.00
4	0.91	0.94	0.92	0.43	0.31	0.36	0.91	0.98	0.94
5	0.79	0.66	0.70	0.54	0.40	0.46	0.82	0.65	0.72
6	0.60	0.60	0.60	0.29	0.21	0.24	0.64	0.57	0.60
7	0.82	0.87	0.84	0.48	0.41	0.44	0.81	0.96	0.88
8	0.91	1.00	0.95	0.53	0.84	0.65	0.94	1.00	0.97
Accuracy	83.52			46.33			85.16		

Table 7: White wine balanced class performance.

	SVM			NB			ANN		
Class	Precision	Recall	F1 score	Precision	Recall	F1 score	Precision	Recall	F1 score
3	1.00	0.99	0.99	0.71	0.42	0.53	1.00	1.00	1.00
4	0.99	0.86	0.92	0.54	0.56	0.55	0.93	0.98	0.95
5	0.96	0.58	0.73	0.36	0.48	0.41	0.81	0.78	0.79
6	0.50	0.96	0.66	0.37	0.11	0.17	0.70	0.63	0.66
7	0.98	0.72	0.83	0.30	0.48	0.37	0.81	0.84	0.83
8	0.99	0.92	0.95	0.37	0.35	0.36	0.93	0.97	0.95
9	1.00	1.00	1.00	0.79	0.91	0.85	1.00	1.00	1.00
Accuracy	86.86			46.68			88.28		

6.3. Discussion

Based on our research question “what wine features are important to get the promising result?” To answer this question we implement the Pearson coefficient correlation matrices and calculate the relationship among all the features, as in red wine correlation matrices Figure 5 and white wine correlation matrices Figure 6. Then we ranked the features based on high correlation with the quality feature. The analysis of groups of features from left to right is implemented, shown in Figure 7 and Figure 8, and from both datasets first 10 features are selected and the last feature is excluded because there is no improvement and it is decreasing the performance of the model. 'residual sugar' feature from red wine datasets and 'free sulfur dioxide' feature from the white wine dataset is excluded for the final implementation of the models.

After identifying the importance of the features we start the implementation of the model. To analyze the performance of the model firstly, we implemented the model on the original data (unbalanced class), as shown in Figure 3, and then implemented the model on the balance class, shown in Figure 4, balancing each class.

In terms of the performance of the prediction model accuracy, precision, recall, and f1 score is examined, as expressed in Table 4 red wine and Table 5 white wine performance analysis results for unbalanced classes for each model is examined, and Table 6 red wine and Table 7 white wine performance analysis results for the balanced classes for each model is examined.

From these unbalancing and balancing classes, we achieved a better performance result on the balanced class for all the models.

Among the three algorithms, the artificial neural network (ANN) algorithm achieved the best performance result from both red and white wine datasets as compare to the support vector machine (SVM) and naïve Bayes (NB) algorithm.

There is other related work that was mentioned in section 2.2, but they differ from this project in different ways.

Kumar, (2020) paper is similar in that they used similar performance measurements and similar machine learning algorithms such as support vector machine and naïve Bayes. The difference is that they trained the model on unbalanced classes and they used all features for the prediction of the model. In terms of performance analysis, they achieved the best of 67.25% accuracy from the support vector machine on the red wine dataset, Er and Atasoy, (2016) has been achieved the best accuracy result from the random forest on 69.90% in the red wine and 71.23% white wine datasets and use the principal components analysis technique for feature selection. Gupta, (2018) has been proposed that all features are not necessary for the prediction instead of selecting only necessary features to predict the wine quality. For that, they used linear regression for determining the dependencies of the target variable. Whereas our model achieved 69.06% accuracy in the red wine dataset and 67.83% accuracy in the white wine dataset from the support vector machine. Then after training, the model on the balanced data and selecting the best hyperparameters the performance of the model is improved and achieved 83.52% accuracy in the red wine and 86.86% accuracy in the white wine. In addition, our model achieved the best 85.16% accuracy in the red wine and 88.28% accuracy in the white wine from the artificial neural network model by applying the Pearson coefficient correlation matrices for the feature selection.

7. Conclusions and Future Work

7.1. Conclusion

This report uses the two types of wine dataset red and white, of Portuguese “Vinho Verde” wine to predict the quality of the wine based on the physicochemical properties.

First, we used oversampling to balance the dataset in the data preprocessing stage to optimize the performance of the model. Then we look for features that can provide better prediction results. For this, we used Pearson coefficient correlation matrices and ranked the features according to the high correlation among the features. After applying the sampling datasets which is balancing dataset the performance of the model is improved. In general, removing irrelevant features of the datasets improved the performance of the classification model. To conclude that the minority classes of a dataset will not get a good representation on a classifier and representation for each class can be solved by oversampling and undersampling to balance the representation classes over datasets.

The accuracy of the support vector machine (SVM) algorithm is 83.52% from the red wine and 86.86% from the white wine, the naïve Bayes (NB) algorithm is 46.33% from the red wine and 46.68% from the white wine, and the artificial neural network (ANN) is 85.16% from the red wine and 88.28% accuracy from the white wine. Among these three machine learning algorithms, we achieved the best accuracy result from the artificial neural network (ANN) on both red and white wine datasets.

Therefore, in the classification algorithms by selecting the appropriate features and balancing the data can improve the performance of the model.

7.2. Future Work

In the future, to improve the accuracy of the classifier, it is clear that the algorithm or the data must be adjusted. We recommend feature engineering, using potential relationships between wine quality, or applying the boosting algorithm on the more accurate method.

In addition, by applying the other performance measurement and other machine learning algorithms for the better comparison on results. This study will help the manufacturing industries to predict the quality of the different types of wines based on certain features, and also it will be helpful for them to make a good product.

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