Predicting Wine Properties Based on Weather Conditions Using Machine Learning Techniques

Sijce Miovska*, Cveta Martinovska Bande*, Natasha Stojkovik*, Milena Taseska-Gjorgjijevski**

* Faculty of Computer Science, Goce Delcev University, Stip, North Macedonia

** Department for Winemaking, Institute of Agriculture, Ss.Cyril and Methodius University, Skopje, North Macedonia

cveta.martinovska@ugd.edu.mk

Abstract — **Wine quality depends on different factors from cultivation to production. The main factors affecting the quality are weather and climate, growing practices of the vineyard and techniques used by winemakers. This paper explores the effectiveness of several machine learning algorithms to predict the quality based on various features. The wine dataset is prepared from a certification and quality assessment laboratory, containing various physicochemical characteristics such as alcohol content, volatile acids, total extracts, residual sugar, among others. Weather conditions, including precipitation levels, daily average temperature, temperatures exceeding 10°C, and relative air humidity, exhibit varying impacts on vineyards during different growth stages. Our analysis shows that Random Forest with SMOTE method outperforms all other classifiers with 73% accuracy. Similar outcomes are achieved using the RUSBoost ensemble method. Furthermore, we investigate how weather conditions impact the characteristics of white and red wines from diverse regions in North Macedonia, each with its own unique climate and soil conditions. Results indicate that high temperatures without precipitation during the ripening period positively affect wine quality. The analysis yielded a Pearson coefficient of -0.11 for the correlation between air humidity and alcohol content, and 0.19 for the correlation between average temperature and residual sugar levels.**

Keywords – classification; predicting wine properties; data preprocessing.

I. INTRODUCTION

In recent years, machine learning techniques have been increasingly used for data analysis [1]. In this study, machine learning algorithms are applied to analyze, visualize, and predict the quality of red and white wines. The wine dataset consists of information about grape types, wine brands, wine cellars, physicochemical properties, and data from sensory tests. Physicochemical laboratories determine the density, alcohol percentage, pH value, sugar residue, total and volatile acids, total and free sulfur, while experts evaluate wine quality through sensory tests. The entire chemical composition of wine reflects various stages of the winemaking process, including grape variety, yeast type, fermentation and storage containers, and enological practices.

Certain studies predominantly use machine learning techniques to evaluate wine quality based on physicochemical data [2][3]. Conversely, another study [4] introduces a predictive model for wine prices that relies on weather data. Some models utilize synthetic data constructed from physicochemical and chemical features [5]. In this study, the authors achieved superior results using AdaBoost and Random Forest (RF) classifiers for wine quality prediction. Their method incorporated 54 physicochemical and chemical features, with 1381 samples generated from 12 original samples using the Synthetic Minority Over-Sampling Technique (SMOTE) method.

Recent research articles have explored the potential of different machine learning algorithms to predict wine quality [6]. Dahal and colleagues [7] analyzed the essential features affecting wine quality and compared the performance of Ridge Regression, Support Vector Machines (SVM), Gradient Boosting Regressor (GBR), and Neural Networks (NN). According to their findings, GBR showed the best results and predicted wine quality with an MSE of 0.3741 and an R value of 0.3741. In [8], the authors analyzed Chilean wines using SVM and various NN models, achieving an accuracy range from 94.4% to 97.8% with NN and above 97% with SVM. Apart from physicochemical features, they also used features such as total phenols and flavonoids. Similarly, in [9], the authors focused on comparing different classification algorithms for wine quality analysis, such as SVM, RF, and NN.

Fuentes and colleagues [10] used wine sensory profiles, including color, anthocyanin content, aroma profiles, astringency, and mouthfeel. They utilized data from near-infrared spectroscopy and weather data to predict wine color. Gómez-Meire and colleagues [11] employed SVM, RF, MLP, K-Nearest Neighbors (KNN), and Naïve Bayes classifiers in a study classifying white grape varieties using gas chromatography data and aroma compounds. They found that RF was able to perfectly classify the grapes, but other classifiers were more accurate with part of the available features. Results from a machine learning study [12] showed that neural network regression analysis successfully predicts wine quality with an error rate of 0.196. Another study [13] compared the results from different classifiers to predict wine quality, with RF achieving 65.83% accuracy, SVM 67.2%, and Naïve Bayes 55.9%.

This article aims to evaluate the performance and accuracy of prediction models generated using machine learning techniques. The study explores the behavior of several algorithms, both used individually and in ensemble learning, to predict wine quality based on physicochemical features and weather conditions. The research relies on a database from an Agricultural Institute quality assessment laboratory, which is not accessible to the public. The weather data are obtained from the Hydrometeorological Service of North Macedonia. Initial attempts with individual classifiers did not yield promising results. Consequently, the study turned to ensemble methods, which can leverage the unique strengths of each classifier.

II. DATA AND METHODS

A. Description of the Dataset

The wine dataset used in this study contains data from the last 3 years, encompassing wines produced in the largest wine regions of North Macedonia. It includes features obtained from a quality assessment laboratory, consisting of physicochemical characteristics such as alcohol content, volatile acids, sulfur dioxide, total acids, total extracts, sugar residue, and others.

The dataset comprises several independent variables and wine quality as the dependent variable, with 371 red wine samples and 346 white wine samples. Table 1 presents the descriptive statistics for white wines.

TABLE I. DESCRIPTIVE STATISTICS FOR WHITE WINES

variable	mean	std	min	25%	50%	75%	max
specific weight	0.992	0.0026	0.989	0.991	0.991	0.992	1.012
alcohol	12.43	1.016	10.35	11.79	12.48	13.13	15.2
total extracts	22.8	6.166	15.6	19.82	21.3	23.7	71.9
sugar	3.24	5.525	1.0	1.0	1.3	3.2	53.6
extract without sugar	20.03	1.673	14.2	19.2	20.2	21.0	28.4
total acidity	5.36	0.593	2.0	5.0	5.3	5.7	7.2
volatile acidity	0.42	0.117	0.2	0.33	0.41	0.49	0.9
total sulfur	102.94	28.765	23.04	83.2	101.12	119.04	198.4
free sulfur	29.7	11.663	1.28	23.04	28.16	34.56	108.8
density	0.99	0.006	0.892	0.989	0.99	0.99	1.01

The variable quality denotes the category of the wine sample [15]. There are 4 categories of wines: wines without geographical indication, regional wines with geographical indication WGO, wines with controlled origin WCO and wines with controlled and guaranteed origin with high quality WCGO. The databases used in this paper do not contain wines of the first category, i.e. wines without geographical indication. There is a class imbalance of the data because the WCGO wines are less represented than the majority class WCO.

Alcohol is one of the main components that determine the quality of the wine. It is the product of alcohol fermentation of grape sugar, and it affects the texture, form, aroma, and the scent of the wine. The alcohol content in wine varies from 8-20 vol%, and it depends on the sugar content in grapes, temperature of fermentation and the type of yeast used in the process.

Wine also consists of volatile acids such as acetic acid, formic acid, butyric acid, propionic acid etc., of which acetic acid is most dominant with 95-98%. Because of that, the content of volatile acids in wine is expressed as g/L acetic acid. Wines with higher content of volatile acids are more prone to spoilage, on the other hand, low content of acetic acid up to 300 mg/L offers the wine more complexity, or bouquet, and in larger quantities it leads to a sharper taste.

SO_2 (Sulphur dioxide) is used for protecting the wine from oxidation through inhibition of oxidase activity. SO_2 also has an antimicrobial activity, as it prevents the growth and activity of dangerous yeasts and bacteria. The Sulphur dioxide is usually added in the must in quantities varying from 50-100 ml/L. During fermentation a part of SO_2 oxidizes to sulfate, and the rest of it binds with other wine components, thus losing its antioxidant properties. When SO_2 is added in must or wine it binds with other components, and all new forms are known as total SO_2. That is why it is necessary to know the free SO_2 during fermentation and storage of the wine.

Total acids are components that give the wine a certain freshness. The content of total acids in grapes or wine is expressed through tartaric acid, which is the most dominant of the organic acids group. Around 90% of the total wine acidity derives from tartaric and malic acid. Young wines contain larger quantities of tartaric acid, which sediments with maturing as salts known as tartrates. The content of total acids in grapes is around 8-12 g/L, while in wine it is around 5.5-8 g/L, and it depends on the type of the grapes. Wines with higher pH value are more prone to oxidation, unlike wines with lower pH values which are biologically more stable.

The total extracts in wines are represented by solid nonvolatile components such as sugars, polyphenols, glycerol etc. The content depends on the type, production technology like maceration period, which is the period of direct contact of the must with different parts of the grapes (epidermis, seeds, fruit). Red wines contain a higher extract content, as their fermentation develops alongside the solid parts (epidermis, seeds, fruit) while white wines have a smaller content because only their must ferments.

Sugar residue is the content of sugar that remains unfermented after fermentation is complete. This includes parts of the disaccharides sucrose and fructose, as well as the monosaccharides galactose, arabinose, ribose, xylose and rhamnose. According to the sugar residue, wines are divided into dry up to 5g/L, semi-sweet from 10-20 g/L and sweet wines around 40-100 g/L.

Meteorological data, such as the amount of precipitation, average daily air temperatures, temperatures above 10°C, relative air humidity, and insulation are included in the wine dataset.

B. Machine Learning Models Included

Several machine learning algorithms are used in this project to analyze wine dataset, such as KNN, Decision Tree, Logistic Regression, and Random Forest. To achieve more accurate predictions, we experimented with two ensemble learning techniques: XGBoost and RUSBoost.

KNN is a simple and intuitive algorithm used for both classification and regression. It is non-parametric and instance-based, meaning it doesn't make any assumptions about the underlying data distribution and uses the entire dataset for prediction. Decision Trees are hierarchical tree-like structures that recursively partition the feature space into regions, based on the feature values, to make decisions.

Logistic Regression is a linear model used for binary classification. It models the probability that an instance belongs to a particular class using the logistic function (sigmoid function), which maps the output of a linear combination of the input features to a value between 0 and 1. Logistic regression can be extended to handle multi-class classification using techniques like one-vs-rest (OvR) or multinomial logistic regression.

Random Forest is an ensemble learning method that constructs a multitude of decision trees during training. Each tree in the forest is trained on a bootstrap sample of the training data and makes decisions based on a random subset of features. In classification, the final prediction is determined by aggregating the predictions of all trees through majority voting. Random Forest is robust against overfitting, as it combines the predictions of multiple trees, and it's less sensitive to noisy data and outliers compared to individual decision trees. Additionally, Random Forest provides estimates of feature importance, which can be useful for feature selection and understanding the data.

XGBoost is a gradient boosting algorithm that uses decision trees as base learners and does not inherently address class imbalance. It builds the model sequentially, with each new tree correcting the errors made by the previous ones. XGBoost can be used with techniques like class weights or sampling methods to handle imbalanced classes. RUSBoost is an ensemble technique that combines random undersampling of the majority class with the boosting algorithm (typically AdaBoost). It is specifically designed to handle imbalanced classes by undersampling the majority class during each boosting iteration, thus giving more weight to the minority class examples.

III. Results and Discussion

A. *Data Processing and Visualization of the Relevance*

Figure 1 represents a correlation heatmap that shows the relationships between different wine features.

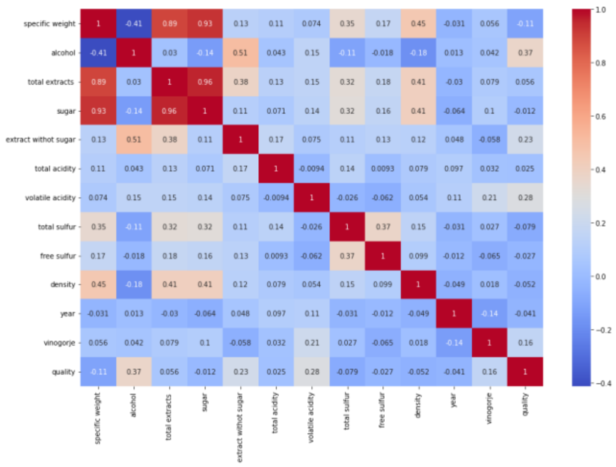

Figure 1. Correlation heatmap for white wine features

Some values are expected, such as the correlation between specific weight and sugar, and specific weight and total extracts. The interesting fact examined in the following text is the association between the level of alcohol and wine quality, as well as the association of volatile acidity and wine quality.

B. *Implemented Machine Learning Methods*

The most common classification algorithms are trained with the datasets, and then the results are compared. Before training, data are normalized using the StandardScaler function defined in the Scikit-learn Python library.

The first classification model was created using K-Nearest Neighbors, and the value of 11 for the parameter k was obtained by plotting the change in accuracy with the change of k.

To evaluate the performance of the classifier we used accuracy and One-Versus-Rest (roc auc ovr) metrics. The results obtained with KNN are represented in Table 2.

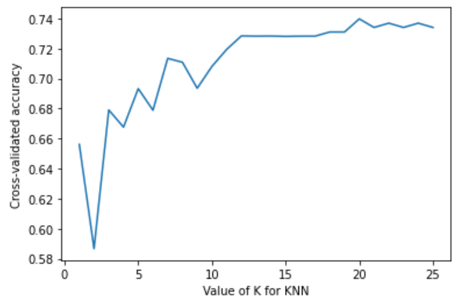

Figure 2. Estimation of parametar k in KNN

As a measure of the overall correctness of the classifier, accuracy represents the proportion of correctly classified instances out of all instances in the dataset. ROC AUC OVR represents the average area under the ROC curve for each binary classifier (one per class) in the OVR scheme and provides an overall measure of the classifier's ability to distinguish between the different classes.

TABLE II. KNN Evaluation for White Wine

	precision	recall	f1-score	support
WGO	1.000	0.235	0.381	17
WCO	0.758	1.000	0.862	50
WCGO	1.000	0.000	0.000	3
accuracy			0.771	70
macro avg	0.919	0.412	0.414	70
weighted avg	0.827	0.771	0.708	70

cross validation score 0.719
cross validation score with roc_auc 0.713
roc_auc_score 0.771

The results show that multi class cross validation score is around 0.72, but the recall of the smallest class is zero. So, the model is biased towards the bigger classes and it is not the best model. Because the number of samples in the classes is not balanced, the better measure is cross validation method with roc_auc_ovr scoring instead of accuracy scoring.

Multinomial Logistic Regression cross-validation score was 0.73, but the recall of the smallest class was still zero. Multinomial Logistic Regression with second degree polynomial features produced better recall for WCGO class and the cross-validation score was 0.71 (Table 3).

TABLE III. LOGISTIC REGRESSION EVALUATION FOR WHITE WINE

	precision	recall	f1-score	support
WCO	0.474	0.529	0.500	17
WGO	0.812	0.780	0.796	50
WCGO	0.333	0.333	0.333	3
accuracy			0.700	70
macro avg	0.540	0.548	0.543	70
weighted avg	0.710	0.700	0.704	70

cross validation score with roc_auc_ovr scoring 0.710
roc_auc_score 0.785

For the Decision Tree classifier, we created three models with different values for the parameter "criterion" (gini, entropy, and log_loss), which measures the quality of the split.

With the Decision Tree classifier and the criterion set to 'gini,' similar results are obtained for the recall, but the accuracy and cross-validation score are lower (Table 4). The models with other values for the parameter "criterion" performed with lower accuracy (0.58 and 0.57).

TABLE IV. DECISION TREE EVALUATION FOR WHITE WINE

	precision	recall	f1-score	support
WCO	0.333	0.471	0.390	17
WGO	0.767	0.660	0.710	50
WCGO	0.333	0.333	0.333	3
accuracy			0.600	70
macro avg	0.478	0.488	0.478	70
weighted avg	0.643	0.600	0.616	70

cross validation score with roc_auc_ovr scoring 0.591
roc_auc_score 0.605

Random Forest classifier produced slightly higher scores for cross validation and roc_auc_score, but the recall for WCGO class was still lower than for the other 2 classes.

We then used GridSearchCV to search for the best combination of the parameters (estimators, maximum depth, minimum samples split, and minimum samples leaf) for Random Forest classifier based on the 'roc_auc_ovr' scoring metric. We used the following parameters:

param_grid ={'n_estimators': [100,200,300], 'max_depth': [None,10,20], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4]}

The best roc_auc_score that we obtained is 0.787 with the following parameters: 'max_depth':None, min_samples _leaf': 2, 'min_samples_split': 2, 'n_estimators': 300.

We obtained similar results with SMOTE algorithm with Random Forest classifier. This algorithm adds synthetic samples to the smallest class. With SMOTE algorithm there is an increase in cross validation score and better recall for the WCGO class (Table 5).

TABLE V. RANDOM FOREST EVALUATION FOR WHITE WINE

	precision	recall	f1-score	support
WCO	0.500	0.529	0.514	17
WGO	0.820	0.820	0.820	50
WCGO	0.500	0.333	0.400	3
accuracy			0.729	70
macro avg	0.607	0.561	0.578	70
weighted avg	0.729	0.729	0.728	70

cross validation score with roc_auc_ovr scoring 0.729
roc_auc_score 0.789

For red wines, we achieved similar results as for the white wines. The best ROC AUC score was obtained with the Random Forest classifier using the SMOTE method, and the main issue was the class imbalance (Table 6).

TABLE VI. RANDOM FOREST EVALUATION FOR RED WINE

	precision	recall	f1-score	support
WGO	0.333	0.267	0.296	15
WCO	0.714	0.800	0.755	50
WCGO	0.571	0.400	0.471	10
accuracy			0.640	75
macro avg	0.540	0.489	0.507	75
weighted avg	0.619	0.640	0.625	75

cross validation score with roc_auc_ovr scoring 0.74
roc_auc_score 0.738

To create more precise predictions, we explored two ensemble learning methods: XGBoost and RUSBoost. Results presented in Table 7 show the roc_auc_score of 0.746 for RUSBoost classifier.

TABLE VII. RUSBOOST EVALUATION FOR WHITE WINE

	precision	recall	f1-score	support
WCO	0.320	0.471	0.381	17
WGO	0.786	0.660	0.717	50
WCGO	0.333	0.333	0.333	3
accuracy			0.600	70
macro avg	0.480	0.488	0.477	70
weighted avg	0.653	0.600	0.619	70

Cross validation score with roc_auc_ovr scoring: 0.702
roc_auc_score: 0.746

Despite achieving a roc_auc_score of 0.83, XGBoost had a recall of zero for the WCGO class due to the class imbalance.

Figure 3 shows the alcohol percent in each quality interval for white wines.

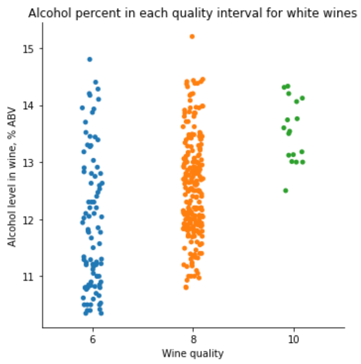

Figure 3. Correlation between alcohol and quality of white wines

Statistical method Analysis of Variance (ANOVA) was used to understand how the quality of wine relates to its alcohol content and whether there are significant differences in alcohol content among different quality categories of wine. Table 8 shows the results of F-statistics and associated p-values for white wines.

Multiple Comparison of Means - Tukey HSD presents the results of Tukey's Honestly Significant Difference (HSD) test, which is a post hoc test used after ANOVA to determine which group means differ from each other.

It compares the mean alcohol content between different quality groups (6, 8, and 10) and indicates whether there are significant differences. The "meandiff" column shows the difference in means between groups. The "p-adj" column shows the adjusted p-values after correcting for multiple comparisons. The "reject" column indicates whether the null hypothesis of no difference in means is rejected for a particular pair of groups. If "reject" is "True", it means there is a significant difference between the means of the corresponding groups.

TABLE VIII. ANOVA FOR ALCOHOL AND QUALITY OF WHITE WINE

OLS Regression Results

Dep. Variable: alcohol	R-squared: 0.141
Model: OLS	Adj. R-squared: 0.136
Method: Least Squares	F-statistic: 28.07
	Prob (F-statistic): 5.15e-12
	Log-Likelihood: -469.74
No. Observations: 346	AIC: 945.5
Df Residuals: 343	BIC: 957.0
Df Model: 2	
Covariance Type: nonrobust	

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	11.9128	0.098	121.615	0.000	11.720	12.105
C(quality)[T.8]	0.6549	0.116	5.662	0.000	0.427	0.882
C(quality)[T.10]	1.6225	0.249	6.512	0.000	1.132	2.113

Omnibus:	12.787	Durbin-Watson:	1.768
Prob(Omnibus):	0.002	Jarque-Bera (JB):	13.363
Skew:	0.461	Prob(JB):	0.00125
Kurtosis:	2.723	Cond. No.	6.29

Means for alcohol by quality of wine

quality	alcohol
WGO	11.912796
WCO	12.567669
WCGO	13.535294

Standard deviation for total alcohol by quality of wine

quality	alcohol
WGO	1.181786
WCO	0.857548
WCGO	0.546147

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
WGO	WCO	0.6549	0.0	0.3826	0.9271	True
WCO	WCGO	1.6225	0.0	1.036	2.209	True
WCO	WCGO	0.9676	0.0002	0.4092	1.526	True

In this context, the Pearson correlation coefficient (r = 0.37) indicates a moderate positive linear relationship between alcohol content and the quality of white wine. The low p-value (approximately 0.00125) indicates that this correlation is statistically significant at a conventional significance level (e.g. α = 0.05). These results suggest that there is a meaningful and statistically significant relationship between alcohol content and the quality of white wine, with higher quality white wines tending to have higher alcohol content.

C. *Influence of Weather on the Wine Quality*

Weather can have a significant influence on wine quality, as it directly affects the grapes' growth, ripening process, and overall composition. Various studies have examined the effects of weather variables on wine quality [16], [17], [18]. The weather conditions have a greater impact on the quality of grapes than the soil or grape variety [19]. Low temperatures lead to low sugar levels [20]. However, excessively high temperatures can also have harmful effects on grapevines [21]. Wine quality in scientific literature is often measured through auction prices [22], [23], [24] or critical evaluations [25], [26]. Weather conditions may have varying effects on grapevines depending on the growth phase. The most important phenological events [27] include the budburst phase, flowering, the onset of grape ripening and the harvest. These phases do not occur simultaneously for different grape varieties. We tested several correlations between physicochemical characteristics of wines and weather conditions.

Figure 4 shows how humidity is related to alcohol for white wines. We obtained Pearson correlation coefficient of -0.1084 for the correlation between humidity and alcohol. The associated p-value of 0.0377 indicates that this correlation is statistically significant at a typical significance level of 0.05.

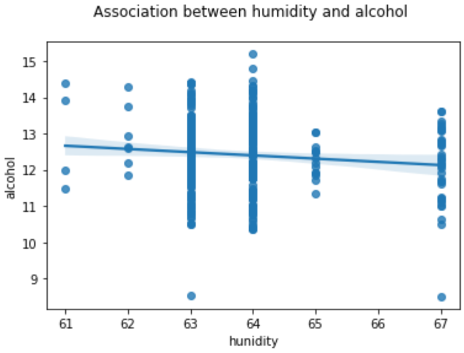

Figure 4. Correlation between humidity and alcohol for white wines

Figure 5 shows a correlation between residual sugar and average temperature for red wines. The positive correlation coefficient between average temperature and residual sugar for red wines (0.1893) indicates a weak positive linear relationship between the variables, and the small p-value (0.000566) suggests that this correlation is statistically significant.

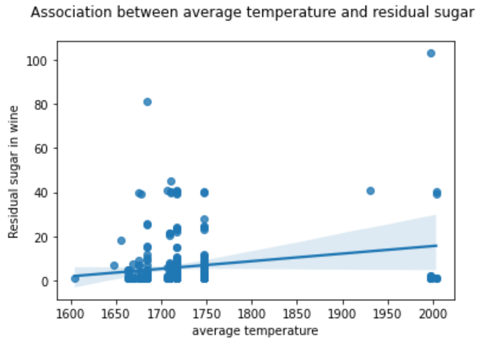

Figure 5. Correlation between residual sugar and average temperature for red wines

IV. CONCLUSION

Several classification algorithms were applied to a multi-class classification problem: K-NN, Logistic Regression with polynomial features, Decision Trees, and Random Forest with the SMOTE method. To achieve more accurate predictions, we tested two ensemble methods: XGBoost and RUSBoost.

After evaluating the cross-validation scores and recall outcomes of each model, we determined that the Random Forest classifier, coupled with the SMOTE method, yielded the most favorable results, boasting a roc_auc_score of 79% and accuracy of 73%. The SMOTE was employed to tackle highly imbalanced classes by generating synthetic minority samples, thereby balancing the dataset. We implemented GridSearchCV to search for the best combination of the parameters and achieved 78.7% roc_auc_score with number of estimators set to 300.

RUSBoost method that combines random under sampling of the majority class with the boosting algorithm achieved auc_roc_score of 75% and accuracy of 60%.

Although the high cross-validation score was achieved, it was observed that the recall results were not representative enough for any of the classes. This indicates that the model's ability to correctly identify instances of each class is not satisfactory. The conclusion drawn is that the model would benefit from more data to improve its performance.

Various factors could contribute to weak correlations between physicochemical characteristics of wines and weather conditions, including the complexity of the relationships, data variability, and the influence of unaccounted factors. Further analysis, considering these factors, may be necessary to gain a deeper understanding of the underlying dynamics.

While temperature and humidity can influence the characteristics of grapes and wines, the relationships with alcohol levels and residual sugar are complex and can be influenced by various factors beyond just these climatic variables. Understanding these dynamics requires considering the influence of multiple factors in vineyard management and winemaking practices.

References

[1] C. Bishop, *Pattern Recognition and Machine Learning*, Springer Science+Business Media, 2006.

[2] P. Bhardwaj, P. Tiwari, W. Parr, and D. Kulasiri, "A machine learning application in wine quality prediction," *Machine Learning with Applications, Elsevier*, vol. 8(1): 100261, January 2022.

[3] P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis, "Modeling wine preferences by data mining from physicochemical properties," *Decision Support Systems*, vol. 47 (4), pp. 547-553, November 2009.

[4] A. Roucher, L. Aristodemou, and F. Tietze, "Predicting wine prices based on the weather: Bourdeaux vineyards in a changing climate, " *Frontiers in Environmental Science*, vol. 10: 1020867, November 2022

[5] Piyush Bhardwaj, Parul Tiwari, Kenneth Olejar, Wendy Parr, Don Kulasiri, "A machine learning application in wine quality prediction, " *Machine Learning with Applications*, vol. 8: 100261, January 2022

[6] Géron A. (2017) Hands-on machine learning with scikit-learn and TensorFlow: Concepts, tools, and techniques to build intelligent systems, http://oreilly.com/safari

[7] Dahal K.R., Dahal J.N., Banjade H., Gaire S. (2021) Prediction of wine quality using machine learning algorithms, *Open Journal of Statistics*, 11, pp. 278-289

[8] Dipak Kumar J., Prajna B., Sirsendu Das A., Anjan M. (2023) Analyzing of salient features and classification of wine type based on quality through various neural network and support vector machine classifiers, *Machine Learning with Applications*, vol.11, article 100219, Elsevier

[9] Shaw B., Suman A.K., Chakraborty B. (2020) Wine quality analysis using machine learning, Advances in Intelligent Systems and Computing, 937, pp. 239-247

[10] Fuentes S., Torrico D.D., Tongson E., Viejo C.G. (2020), Machine learning modeling of wine sensory profiles and color of vertical vintages of pinot noir based on chemical fingerprinting, weather and management data, *Sensors (Switzerland)*, 20 (13)

[11] Gómez-Meire S., Campos C., Falqué E., Díaz F., Fdez-Riverola F., (2014) Assuring the authenticity of northwest Spain white wine varieties using machine learning techniques, *Food Research International*, 60, pp. 230-240

[12] Gupta Y. (2018) Selection of important features and predicting wine quality using machine learning techniques, *Procedia Computer Science*, 125, pp. 305-312

[13] Kumar S., Agrawal K., Mandan N. (2020) Red wine quality prediction using machine learning techniques, *International Conference on Computer Communication and Informatics, ICCCI 2020*

[14] Mahima Gupta U., Patidar Y., Agarwal A., Singh K.P. (2020) Wine quality analysis using machine learning algorithms, *Lecture Notes in Networks and Systems*, 106, pp.11-18

[15] Wines of Macedonia, published by Association Wines of Macedonia (accessed January 2024)

https://tikves.com.mk/wp-content/uploads/2022/02/Wines-of-Macedonia-Brochure_pdf.pdf

[16] Jones, G. V., and Davis, R. E. (2000). Climate influences on grapevine phenology, grape composition, and wine production and quality for Bordeaux, France. *Am. J. Enology Vitic.* 51 (3), pp.249–261.

[17] Corsi, A., and Ashenfelter, O. (2019). Predicting Italian wine quality from weather data and expert ratings. *J. Wine Econ.* 14 (3), pp.234–251.

[18] Biss, A., and Ellis, R. (2021). Modelling Chablis vintage quality in response to inter-annual variation in weather. *OENO One* 55 (3), pp.209–228.

[19] Van Leeuwen, C., Trégoat, O., Choné, X., Bois, B., Pernet, D., and Gaudillère, J.-P. (2009). Vine water status is a key factor in grape ripening and vintage quality for red Bordeaux wine. How can it be assessed for vineyard management purposes? *OENO One* 43 (3), pp.121–134.

[20] Gambetta, G. A., and Kurtural, S. K. (2021). Global warming and wine quality: Are we close to the tipping point? *OENO One* 55 (3), pp.353–361.

[21] Pérez-Magariño, S., and González-San José, M. L. (2006). Polyphenols and colour variability of red wines made from grapes harvested at different ripeness grade. *Food Chem.* 96 (2), pp.197–208.

[22] Jones, G. V., and Storchmann, K.-H. (2001). Wine market prices and investment under uncertainty: An econometric model for Bordeaux Crus Classés. *Agric. Econ.* 26 (2), pp.115–133.

[23] Jones, G. V., White, M. A., Cooper, O. R., and Storchmann, K. (2005). Climate change and global wine quality. *Clim. Change* 73 (3), 319–343. doi:10.1007/s10584-005-4704-2

[24] Haeger, J. W., and Storchmann, K. (2006). Prices of American pinot noir wines: Climate, craftsmanship, critics. *Agric. Econ.* 35 (1), pp.67–78.

[25] Baciocco, K.A., Davis, R.E.,and Jones, G.V.(2014). Climate and Bordeaux wine quality:Identifying the key factors that differentiate vintages based on consensus rankings. *J.Wine Res.*25(2), pp. 75–90.

[26] Almaraz, P. (2015). Bordeaux wine quality and climate fluctuations during the last century: Changing temperatures and changing industry. *Clim. Res.* 64 (3), pp.187–199.

[27] Lancashire, P. D., Bleiholder, H., Boom, T. V D, Langeluddeke, P., Stauss, R., Weber, E., et al. (1991).A uniform decimal code for growth stages of crops and weeds.*Ann.Appl.Biol.*119(3),pp.561–60.