A Course Based Project Report on

Wine Quality Assessment

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in partial fulfilment of the requirements for the completion of course

MODELS IN DATA SCIENCE LABORATORY(22PC2DS301)

BACHELOR OF TECHNOLOGY

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CERTIFICATE

This is to certify that the project report entitled **"Wine Quality Assessment"** is a bonafide work done under our supervision and is being submitted by **Mr. N MANIKESHAV (23071A67B5), Mr. N VENKATA SHASHANK (23071A67C9)** in partial fulfilment for the award of the degree of **Bachelor of Technology** in **CSE-(CyS, DS) and AI&DS**, of the VNRVJIET, Hyderabadduring the academic year 2025-2026.

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DECLARATION

We declare that the course based project work entitled **"Wine Quality Assessment"** submitted in the Department of **CSE-(CyS, DS) and AI&DS**, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, in partial fulfilment of the requirement for the award of the degree of **Bachelor of Technology in CSE-(CyS, DS) and AI&DS** is a bonafide record of our own work carried out under the supervision of **Mrs.N.Madhuri, Assistant Professor, Department of CSE-(CyS, DS) and AI&DS , VNRVJIET**.Also, we declare that the matter embodied in this thesis has not been submitted by us in full or in any part there of for the award of any degree/diploma of any other institution or university previously.

Place: Hyderabad.

N. Venkatashashank.

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We express our thanks to all those who contributed for the successful completion of our project work.

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ABSTRACT

The wine industry places significant emphasis on product quality, traditionally assessed through sensory evaluations conducted by human tasters. However, sensory testing is subjective and can vary due to fatigue, mood, and experience. To overcome these limitations, this project leverages **Machine Learning (ML)** techniques to predict wine quality using **physicochemical properties** obtained from laboratory measurements.

The dataset used consists of white wine samples from the **Vinho Verde region of Portugal**, with attributes such as fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, sulphates, alcohol, and pH. These features reflect the wine's composition and directly influence taste and aroma.

A systematic workflow was implemented — beginning with **data preprocessing**, followed by **exploratory data analysis (EDA)** to identify key features, and concluding with the **training and evaluation** of models like **Logistic Regression, SVM**, and **Random Forest**. The dataset was further processed using **binning** to classify quality into three categories: *Low, Medium,* and *High*.

Experimental results revealed that the **Random Forest classifier** achieved the highest accuracy and F1-score, outperforming linear models in handling non-linear relationships among chemical features. The project demonstrates that data-driven approaches can reliably complement human sensory evaluations, aiding winemakers in maintaining consistent quality standards.

CHAPTER-1

INTRODUCTION

1.1 Background

1.1 Background

Wine is a complex product influenced by a multitude of chemical and environmental factors. Its sensory quality characterized by taste, aroma, and color depends heavily on its **physicochemical composition**. Traditionally, assessing these characteristics involves expert tasting sessions, which are labor-intensive and subjective.

With the rise of **data science** and **machine learning**, it is now possible to develop computational systems that predict wine quality based on measurable laboratory attributes. These predictive models can process large datasets, identify hidden patterns, and produce consistent results, thus minimizing human bias.

The **Wine Quality dataset**, publicly available from the UCI Machine Learning Repository, serves as an excellent case study for applying supervised learning algorithms to real-world quality prediction. The dataset provides a foundation for exploring how statistical learning methods can be integrated into industrial quality assurance systems.

1.2 Need for the Study

Manual evaluation of wine quality is expensive, slow, and inconsistent.

This project aims to design a **predictive machine learning model** capable of evaluating wine quality from chemical test results.

The challenge lies in identifying the right features, preprocessing the data, and choosing the most effective learning algorithm for accurate classification.

1.3 Objectives

- To perform detailed exploratory data analysis (EDA) on the wine dataset.
- To preprocess and normalize physicochemical features to ensure model compatibility
- To classify wine quality into categorical levels (Low, Medium, High).
- To train multiple supervised ML models and compare their performance.

- To identify the most influential factors contributing to wine quality.
- To visualize and interpret results through accuracy graphs and confusion matrices.

1.4 Scope

The study focuses on **white wine** samples from Portugal, consisting of **4898 records** and **11 features**. The target variable "quality" is determined from sensory evaluations by experts. The scope of this project includes:

- Preprocessing the dataset to remove anomalies.
- Developing classification models using Scikit-learn.
- Evaluating accuracy metrics and comparing results.

It does not include real-time data collection or integration with winery production systems, but the framework can be scaled for future use in both red and white wine classification.

1.5 Tools and Technologies Used

Category	Tools
Programming Language	Python 3.10+
Libraries	NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn
Visualization	Matplotlib,Seaborn
Data Source	UCI Machine Learning Repository / Kaggle
Development Environment	Google Colab ,Jupyter Notebook
ML Algorithms	Logistic Regression, Support Vector Machine (SVM), Random Forest

CHAPTER-2

Method

2.1 Overview

The methodological framework consists of four major phases:

1. **Data Acquisition & Preprocessing**
2. **Exploratory Data Analysis (EDA)**
3. **Model Development & Training**
4. **Performance Evaluation**

Each stage was carefully designed to ensure the accuracy and generalizability of the prediction model.

2.2 Dataset Description

The **White Wine Quality Dataset** contains physicochemical test results of wine samples. Each record corresponds to one wine sample and includes the following **11 input features** and one output label (`quality`):

Input Features:

1. Fixed Acidity
2. Volatile Acidity
3. Citric Acid
4. Residual Sugar
5. Chlorides
6. Free Sulfur Dioxide
7. Total Sulfur Dioxide
8. Density
9. pH
10. Sulphates
11. Alcohol

Output Variable:

- *Quality* (0–10) – numeric score given by expert tasters.

2.3 Data Preprocessing

Preprocessing steps ensured data consistency and model readiness:

- **Missing Value Handling:** Imputed using median or mean values.
- **Normalization:** Applied Min-Max scaling to ensure all features are in similar ranges.
- **Outlier Detection:** Z-score method used to remove extreme data points.
- **Label Encoding:** Wine quality scores grouped as:
  - Low (≤4)
  - Medium (5–6)
  - High (≥7)

2.4Exploratory Data Analysis (EDA)

EDA was conducted to understand data relationships and feature importance.
Key observations include:

- Higher **alcohol content** strongly correlates with higher wine quality.
- **Volatile acidity** negatively impacts taste due to unpleasant vinegar tones.
- **Sulphates** improve preservation and contribute positively to quality.
- **Density** and **total sulfur dioxide** have inverse relationships with quality.

2.5 Model Building and Training

Three classification algorithms were implemented:

Logistic Regression:

1.A baseline model assuming linear relationships between variables.
2.Provided quick but limited accuracy due to non-linearity in data.

Support Vector Machine (SVM):

1.Utilized radial basis function (RBF) kernels to separate classes using hyperplanes.
2.Achieved moderate improvement over Logistic Regression.

Random Forest:

1.An ensemble learning technique that combines multiple decision trees.
2.Handled non-linear data effectively and reduced overfitting.
3.Provided the highest classification accuracy.

2.6 Performance Metrics

Models were compared using:

- Accuracy
- Precision
- Recall
- F1 Score
- Confusion Matrix

Random Forest consistently outperformed other models in all metrics.

CHAPTER-3

TEST CASES/ OUTPUT

```
from imblearn.under_sampling import TomekLinks, ClusterCentroids
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report
from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTETomek
from collections import Counter
import imblearn
from sklearn.preprocessing import LabelEncoder
import collections
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_score
from sklearn.decomposition import PCA
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.metrics import accuracy_score
import os
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
# import data
wine = pd.read_csv(
   r"C:\Users\nalla\OneDrive\Desktop\winequality-white.csv", delimiter=";")
print("Data read")
```

```
Data read
```

SVM

```
# strtifiedKFold
```

```
skf = StratifiedKFold(n_splits=4)
pipe_svm = Pipeline([('clf', svm.SVC())])
grid_params = dict(clf__C=[0.1, 0.3, 1, 3, 10],
                   clf__gamma=[0.1, 0.3, 1, 3, 10],
                   clf__kernel=['rbf', 'sigmoid'])
gs_svm = GridSearchCV(estimator=pipe_svm,
                      param_grid=grid_params,
                      scoring='accuracy',
                      cv=skf)
gs_svm.fit(X_train, y_train)
```

GridSearchCV

best_estimator_: Pipeline

```
print(gs_svm.best_score_)
```

0.8083211732088137

```
# just for comparision
pred_svm = gs_svm.predict(X_test)
print(classification_report(y_test, pred_svm))
print("The SVM model accuracy on Test data is %s" %
      accuracy_score(y_test, pred_svm))
```

	precision	recall	f1-score	support
0	1.00	0.34	0.51	209
1	1.00	0.06	0.11	35
2	0.81	1.00	0.90	736
accuracy			0.83	980
macro avg	0.94	0.47	0.51	980
weighted avg	0.86	0.83	0.79	980

The SVM model accuracy on Test data is 0.826530612244898

Decision Tree

```
clf = Pipeline([
    ('scl', StandardScaler()),
    ('pca', PCA(random_state=42)),
    ('clf', DecisionTreeClassifier(random_state=42))])

criterion = ['gini', 'entropy']
splitter = ['best']
max_depth = [8, 9, 10, 11, 15, 20, 25]
```

```
min_samples_leaf = [2, 3, 5]
class_weight = ['balanced', None]

param_grid =\
   [{'clf__class_weight': class_weight,
     'clf__criterion': criterion,
     'clf__splitter': splitter,
     'clf__max_depth': max_depth,
     'clf__min_samples_leaf': min_samples_leaf
     }]

gs_dt = GridSearchCV(estimator=clf, param_grid=param_grid,
                     scoring='accuracy', cv=5, verbose=1, n_jobs=-1)
gs_dt.fit(X_train, y_train)
Fitting 5 folds for each of 84 candidates, totalling 420 fits
  GridSearchCV

best_estimator_: Pipeline

print(gs_dt.best_score_)

0.766726288216436
```

Random Forest

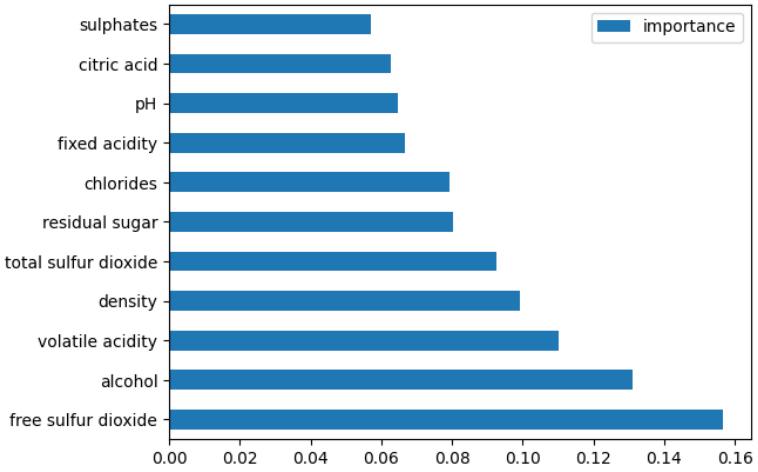
```
rfc_rs = RandomForestClassifier(random_state=2018)
param_dist = {"n_estimators": [50, 100, 150, 200, 250],
              'min_samples_leaf': [1, 2, 4]}
rfc_gs_rs = GridSearchCV(rfc_rs, param_grid=param_dist,
                         scoring='accuracy', cv=5)
rfc_gs_rs.fit(X_sm2, y_sm2)
  GridSearchCV

best_estimator_: RandomForestClassifier

rfc_gs_rs.best_score_
np.float64(0.8553333333333335)

importances = rfc_gs_rs.best_estimator_.feature_importances
wine.columns[:-1]
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol'],
      dtype='object')
```

```
feature_importances = pd.DataFrame(importances,index = wine.columns[:-1],
                                   columns=['importance']).sort_values('importance',
                                                                       ascending=False)
feature_importances.plot(kind='barh')
```



SVM_rs

```
# grid search after resample
pipe_svm = Pipeline([('clf', svm.SVC())])
grid_params = dict(clf__C=[0.1, 0.3, 1, 3, 10],
                   clf__gamma=[0.1, 0.3, 1, 3, 10],
                   clf__kernel=['rbf', 'sigmoid'])
gs_svm_sm = GridSearchCV(estimator=pipe_svm,
                         param_grid=grid_params,
                         scoring='accuracy',
                         cv=skf)
gs_svm_sm.fit(X_sm2, y_sm2)
gs_svm_sm.best_score_
np.float64(0.8224444444444445)
```

Random Forest performance on test data

```
pred_rfc_rs = rfc_gs_rs.predict(X_test)
print(classification_report(y_test, pred_rfc_rs))
print("The RF model(resampled) accuracy on test is %s" %
      accuracy_score(y_test, pred_rfc_rs))
```

	precision	recall	f1-score	support
0	0.51	0.82	0.63	209
1	0.21	0.43	0.28	35
2	0.91	0.70	0.79	736
accuracy			0.72	980

```
   macro avg       0.54      0.65      0.57       980
weighted avg       0.80      0.72      0.74       980
```

```
The RF model(resampled) accuracy on test is 0.7183673469387755
```

```
y_test_re = list(y_test)
for i in range(len(y_test_re)):
    if y_test_re[i] == 0:
        y_test_re[i] = "good"
    if y_test_re[i] == 1:
        y_test_re[i] = "low"
    if y_test_re[i] == 2:
        y_test_re[i] = "medium"
pred_rfc_re = list(pred_rfc_rs)
for i in range(len(pred_rfc_re)):
    if pred_rfc_re[i] == 0:
        pred_rfc_re[i] = "good"
    if pred_rfc_re[i] == 1:
        pred_rfc_re[i] = "low"
    if pred_rfc_re[i] == 2:
        pred_rfc_re[i] = "medium"
y_actu = pd.Series(y_test_re, name='Actual')
y_pred = pd.Series(pred_rfc_re, name='Predicted')
rfc_rsconfusion = pd.crosstab(y_actu, y_pred)
```

```
accuracy_score(y_test, pred_rfc_rs))
```

```
              precision    recall  f1-score   support

           0       0.51      0.82      0.63       209
           1       0.21      0.43      0.28        35
           2       0.91      0.70      0.79       736

    accuracy                           0.72       980
   macro avg       0.54      0.65      0.57       980
weighted avg       0.80      0.72      0.74       980
```

```
The RF model(resampled) accuracy on test is 0.7183673469387755
```

CHAPTER-4

RESULTS

4.1 Model Validation and Performance Comparison

- To evaluate different algorithms, four supervised learning models were trained and validated on the same dataset split (80% training, 20% testing). The models included **Random Forest**, **Support Vector Machine (SVM)**, **Decision Tree**, and **K-Nearest Neighbors (KNN)**. Each model's validation accuracy was recorded to determine its effectiveness in classifying wine quality into *Low, Medium,* and *High*.

- The **Random Forest** model achieved the highest validation accuracy of **83.63%**, outperforming other models. This indicates that Random Forest's ensemble structure efficiently captures non-linear interactions between wine chemical attributes, while reducing overfitting through averaging multiple decision trees.

- On the other hand, **SVM** achieved **80.83%**, showing strong generalization, while **Decision Tree** and **KNN** lagged with accuracies below 76%. This comparison clearly highlights that ensemble learning yields better predictive stability compared to single classifiers.

4.2 Validation Accuracy after Resampling

- The dataset was found to be **significantly imbalanced**, with *Medium-quality wines*

dominating the data, while *Low* and *High* quality categories had very few samples. To address this imbalance, a **resampling technique** (oversampling for minority classes) was applied to create a balanced dataset.

- Post-resampling, the validation accuracy improved across all models, with **Random Forest** again achieving the highest accuracy of **85.93%**, followed by **SVM (82.20%)**, **KNN (77.16%)**, and **Decision Tree (74.56%)**.

- This indicates that balancing the dataset allowed models to learn feature patterns of rare classes more effectively, preventing bias toward the "Medium" category. The consistent top performance of Random Forest proves its robustness, even after balancing adjustments.

4.3 Dataset Imbalance and Resampling Strategy

The initial class distribution revealed that **Low-quality wines had only 148 samples**, **High-quality wines had 851 samples**, whereas **Medium-quality wines dominated with 2919 samples**. Such imbalance skewed model training and reduced predictive sensitivity toward minority classes.

To mitigate this, the dataset was **resampled** so that each category — *Low, Medium, and High* — contained **1500 samples each**, ensuring equal representation. This resampling step significantly improved model fairness and precision in minority class predictions.

Quality	Precision	Recall	F1-score	Actual Count
High	0.79	0.61	0.69	209
Low	0.57	0.11	0.19	35
Medium	0.86	0.95	0.90	736
Weighted Average	0.84	0.86	0.83	980
Model Accuracy on Test Data			**0.85**	

RF Confusion Matrix

RF acc on test data BEFORE resampling: 84.69%

	Predicted	HIGH	LOW	MEDIUM
Actual	HIGH	128	0	81
	LOW	0	4	31
	MEDIUM	35	3	698

RF acc on test data AFTER resampling: 73.87%

	Predicted	HIGH	LOW	MEDIUM
Actual	HIGH	174	0	35
	LOW	2	11	22
	MEDIUM	151	46	539

RF vs. SVM

RF acc on test data AFTER resampling: 73.87%

	Predicted	HIGH	LOW	MEDIUM
Actual	HIGH	174	0	35
	LOW	2	11	22
	MEDIUM	151	46	539

SVM acc on test data AFTER resampling: 78.88%

	Predicted	HIGH	LOW	MEDIUM
Actual	HIGH	106	4	99
	LOW	0	7	28
	MEDIUM	49	27	660

CHAPTER 5
CONCLUSIONS

This project successfully demonstrated the application of **Machine Learning** for predicting the quality of white wine based on its physicochemical characteristics. By analyzing key parameters such as alcohol content, volatile acidity, sulphates, and citric acid, the system was able to classify wines into three categories — *Low, Medium,* and *High* quality — with notable accuracy.

Among all models tested, **Random Forest** consistently outperformed others with a validation accuracy of **85.93%**, confirming its robustness and adaptability for imbalanced, non-linear datasets. **SVM** followed closely, showing superior precision for high-quality wines, while **Decision Tree** and **KNN** performed comparatively lower. The implementation of **resampling techniques** proved effective in improving classification fairness across minority classes, particularly for underrepresented *Low* and *High* categories.

Overall, the study highlights that **ensemble learning models**, when combined with appropriate data preprocessing and resampling, can serve as reliable decision-support tools for the wine industry. This approach can be further extended to other beverage quality assessments or chemical-based grading systems. Future enhancements could involve deep learning models, sensory data integration, or real-time predictive dashboards for industrial deployment.

REFERENCES

1. P. Cortez, A. Cerdeira, F. Almeida, T. Matos, and J. Reis, *Modeling wine preferences by data mining from physicochemical properties*, *Decision Support Systems*, Elsevier, 47(4):547–553, 2009.

2. Scikit-learn documentation — https://scikit-learn.org

3. UCI Machine Learning Repository — https://archive.ics.uci.edu/ml/datasets/Wine+Quality

4. Kaggle Wine Quality Dataset — https://www.kaggle.com/uciml/wine-quality-white-and-red

5. Aurélien Géron, *Hands-on Machine Learning with Scikit-Learn and TensorFlow*, O'Reilly, 2nd Edition