

**WINE QUALITY PREDICTION USING FUZZY
INFERENCE MODEL**

BY

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**BEING A PROJECT SUBMITTED TO
DEPARTMENT OF COMPUTER SCIENCE,
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OF BENIN IN PARTIAL FULFILLMENT OF
REQUIREMENTS FOR THE AWARD OF
BACHELOR DEGREE (B.Sc) COMPUTER SCIENCE**

JULY, 2021.

CERTIFICATION

This is to certify that **MBAKA NZUBE EMMANUEL** with **PSC1607303** carried out this project work under my supervision and it is adequate in scope and content for the award of the University of Benin Bachelor of Science in Computer Science.

DR. (MRS.) R.O. OSASERI
(Project Supervisor)

DATE

APPROVAL

This project work is hereby approved by the Department of Computer Science in partial fulfillment of the requirement for the award of Bachelor of Science (B.Sc.) Degree in Computer Science of the University of Benin.

PROF. F.I. AMADIN
(Head of Department)

DATE

-

DEDICATION

This project work is dedicated to the Almighty for His grace and mercy, my parents Mr. and Mrs. Mbaka and my siblings.

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ABSTRACT

Fuzzy inference systems (FIS) are particularly suited for aggregating multiple data to feed multi-variables decision support systems. Moreover, wine quality is a complex concept that refers to the simultaneous achievement of optimal levels in many parameters, thus single wine attributes spatial data are not adequate to define wine suitability for a specific end use. The aim of this study was to design and implement a fuzzy inference system on wine quality prediction using physiochemical parameters from wine dataset.

The proposed system adopted the conventional fuzzy inference system which consists of four major components which are: knowledge acquisition, knowledge base, fuzzy inference engine and a user interface. The dataset is fuzzified into variables that were used to develop rule for the classification of wine quality. The fuzzy inference system followed three transformation stages; fuzzification, rule based and defuzzification processes. The model was implemented using C#, programming language and MYSQL as the relational data base management. The model was developed on window Microsoft system.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

This study intends to predict the quality of wine based on physiochemical data. What is meant by quality of wine can be difficult to articulate, but one such definition is that “ideally, it should be related to intrinsic visual, taste, or aroma characters which are perceived as above average for that type of wine.

Wine is an alcoholic beverage made from fermented grapes (Johnson, 1989). Yeast consumes the sugar in the grapes and converts it to ethanol, carbon dioxide, and heat. Different varieties of grapes and strains of yeasts produce different styles of wine. These variations result from the complex interactions between the biochemical development of the grape, the reactions involved in fermentation, and the production process (Spilling *et al*; 2008). Many countries enact legal appellations intended to define styles and qualities of wine. These typically restrict the geographical origin and permitted varieties of grapes, as well as other aspects of wine production. Wines not made from grapes include rice wine and fruit wines such as plum, cherry, pomegranate, currant and elderberry

Recent research suggests that the regular and moderate consumption of wine promotes both short-term and long-term cardio-protective effects. For example,

regular wine consumption prolongs and maintains these short-term cardio-protective effects on blood clotting, on the plasma concentration of cholesterol, and on the ability of the blood vessel wall to contract and relax (The Australian Wine Research Institute, 2009). Thus Wine is one of the most valuable beverages in the world and it has a wide market all over the world.

Wine is a complex product, and its composition depends on many and diverse factors such as grape variety, climatic conditions and enological practices. All of them have an important influence on the quality of the wine, and they are very important in the characterization and differentiation of wines, with applications to the detection of frauds (Arvanitoyannis *et al*; 1999). In ancient times the quality and origin of wine is determined by wine experts.

In recent years there is a modest increase in the wine consumption as it has been found that wine consumption has a positive correlation to the heart rate variability (Janszky *et al*, 2005). With the increase in the consumption wine industries are looking for alternatives to produce good quality wine at less cost. Different wines have different purposes. Although most of the chemicals are same for different type of wine based on the chemical tests, the quantity of each chemicals have different level of concentration for different type of wine. These days it is really important to classify different wine for quality assurance (Janszky *et al*, 2005) (Preedy, and MendezIn 2016). In the past due to lack of technological resources it

become difficult for most of the industries to classify the wines based on the chemical analysis as it takes lot of time and also need more money. These days with the advent of the expert system techniques it is possible to classify the wines as well as it is possible to figure out the importance of each chemical analysis parameters in the wine and which one to ignore for reduction of cost. The performance comparison with different feature sets will also help to classify it in a more distinctive way

The purpose of this study is to design and implement a fuzzy inference system on wine quality prediction using physiochemical parameters.

1.2 STATEMENT OF THE PROBLEM

An accurate evaluation of the wine quality is of importance for vintners to perform wine classification. However, since wine quality is influenced by numerous factors such as grape varieties, yeast strains, wine making technologies and human experiences in evaluating wine quality is the main challenge for both the food industry and wine science community; traditionally, wine quality is given by human experts or obtained by analyzing chemical compounds in the wine (Charters and Pettigrew, 2007). Nevertheless, besides the issues like time consuming and complexity, these methods sometimes cannot meet the requirements when wine makers want to know the quality before the wine has

been vinified, for example, predicting wine quality at the time of selecting grapes (Cortez et al; 2009). The use of fuzzy inference system for classifying wine quality will be more efficient than traditional methods of testing wine quality.

1.3 AIMS AND OBJECTIVE

The aim of this study is to design and implement a fuzzy rule based model for the classification of wine quality based on their physiochemical parameters.

The specific objectives are:

1. To model a fuzzy inference system (FIS) for the classification of wine quality based on their physiochemical parameters.
2. To test and evaluate the accuracy of the model.

1.4 RESEARCH SCOPE OF STUDY

The study covers only the classification of red wine quality using their physiochemical parameters. It does not cover any other alcoholic beverages other than red wine.

1.5 SIGNIFICANT OF STUDY

The significant of this study includes; the use of expert wine taster ability into a fuzzy rule base inference classification system that can be used by the winery

community in wine production. This can now be achieved without the physical presence of these human experts.

1.6 RESEARCH METHODOLOGY

1. A careful review was carried out on related work on wine quality and classification.
2. The data set for this study is publicly available for research purposes at <https://archive.ics.uci.edu/ml/datasets/Wine+Quality>. The data set comprised of 11 physiochemical parameters of wine quality.
3. The data set were fuzzified into variables that were used to develop rule for the classification of wine quality. The fuzzy inference system followed three transformation stages; fuzzification, rule based and defuzzification processes.
4. The model was implemented using C#, programming language and MYSQL as the relational data base management. The model was developed on window Microsoft system.

CHAPTER TWO

LITERATURE REVIEW

2.1 WINE

Wine is defined by Robinson (2006) as the “alcoholic beverage obtained from the fermentation of the juice of freshly gathered grapes, the fermentation taking place in the district of origin according to local tradition and practice”. As also pointed out by this author, wine can be made from fruits other than grapes but most of these fruits have less fermentable sugars and hence the need to add sugar from other sources. Wines made from grapes are either made from single grapes or blends (Gutiérrez et al., 2011). Regardless of whether wine is made from a single or a blend of grapes, the end product of grape juice fermentation is a complex mixture of many compounds with water being the predominant component (Jackson, 2014).

Wine quality is usually discussed in terms of the relationships among its components and its sensory properties (Gawel et al., 2007; Landon et al., 2008; Lund et al., 2009; Gawel et al., 2013). Previous research has shown that the sensory properties of the wine are not only related to the individual concentrations of wine components, but also the interactions among these constituents (Jones et al., 2008; Pozo-Bayon and Reineccius, 2009; Villamor et al.,

2013b). The sensory and chemical qualities of wines have been studied using both sensory and instrumental approaches (Villamor et al., 2013a; Baker and Ross, 2014). Besides the use of both consumer and trained sensory evaluation panels to characterize wine quality, the use of novel instrumentation to evaluate wine quality has also been explored. The use of electronic tongues and electronic noses has been documented in the literature as methods to enhance understanding of wine quality (Buratti et al., 2007; Gil-Sánchez et al., 2011; Cosio et al., 2012).

This review examines the current state of knowledge of the influence of wine components on the sensory and chemical properties of wines as determined by both instrumental and sensory approaches.

2.2 COMPOSITION OF WINE

According to the International Organization of Vine and Wine (OIV), wine is a food product exclusively obtained by total/partial fermentation from fresh grapes or the must obtained from pressed/impressed grapes. From the chemical point of view, wines are a complex beverage consisting of water, sugar, amino acids, ethanol, polyphenolic compounds, anthocyanins and organic/inorganic substances (Karataş et al., 2015). As a result, wine composition varies widely according to grape variety and the winemaking process. Matrix Components Water: The most abundant constituent of wine is water, composing ~87% by volume (Jackson,

2014). Water functions to provide the flow properties of wine and serves as the medium in which the other constituents are dispersed. Freshly harvested grapes provide the source of water in wines. However, under some processing conditions, water may be added to wines in a process known as watering back (Harbertson et al., 2009). Alcohols: Wine is composed of different types of alcohols, including methanol, ethanol, sugar alcohols, fusel alcohols, diols and polyols (Fugelsang and Edwards, 2007; Zamora, 2009; Jackson, 2014). These concentrations of these alcohols range from trace amounts (methanol and sugar alcohols) to substantial quantities (ethanol) and have different functions in wine. Ethanol is the next most abundant component of wine after water and the major product of alcoholic fermentation. Under standard fermentation conditions, ethanol can accumulate up to 14-15% (Jackson, 2014). Its concentration in wine depends on the initial sugar levels in the grapes at harvest and the extent to which fermentation is allowed to proceed (Margalit, 2004; Henderson and Rex, 2007). The significance of ethanol to wine is seen in its contribution to the stability, ageing, and extraction of grape constituents, its participation in chemical reactions, and its contribution to the sensory properties of the wine (Robinson, 2006). Ethanol provides microbial stability to wines through its antimicrobial action. The ability of *Saccharomyces cerevisiae* to survive the ethanol environment in wines compared to spoilage yeasts and bacteria ensures that ethanol prohibits the growth of most of the

microbial populations that would otherwise pose a spoilage risk to wine (Fugelsang and Edwards, 2007). However, while many microorganisms are not ethanol tolerant, some microbes including *Zygosaccharomyces bailii* do display ethanol tolerance up to 18% (v/v) (Fugelsang and Edwards (2007). Ageing of wine is characterized by the development of complexity of wine. Ethanol contributes to this process by reacting with organic acids to produce esters and maintaining this equilibrium in favor of ester formation (Jackson, 2014). The sensory impact of ethanol on wine includes a contribution to sweetness (Zamora et al., 2006), burning mouthfeel (Gawel et al., 2007), perception of viscosity (Nurgel and Pickering, 2005) and its influence on the volatility of aroma compounds (Villamor and Ross, 2013).

Residual Sugar: The unfermented sugars remaining in a finished wine are called residual sugar. They are present as both fermentable (glucose and fructose) and unfermentable (pentoses like arabinose and rhamnose) sugars (Robinson, 2006; Jackson, 2014). Generally, the concentration of residual sugars in wines influences whether the wine is considered “sweet” or “dry”, even though other matrix components can contribute to the perceived sweetness of wines. Wines with residual sugar concentrations less than 0.2% (w/w) are not detectable as sweet while very sweet wines can have residual sugars more than 10% (Robinson, 2001). Unfermented sugars may remain in wines for several reasons, including

differences in the sugar utilization by different yeast strains, variation in the nutrient composition of grape musts, diversity and competition among microbial populations during fermentation and fermentation temperatures (Robinson, 2001; Fugelsang and Edwards, 2007). The sensory impact of residual sugars is the sweet taste of the wine but also provides a balance with the acidity of the wine (Zrally, 2011). Polyphenolic Compounds: Polyphenolics are a diverse group of compounds which originate mainly from the grapes (skin and seeds), with small concentrations being extracted from the oak cooperage and trace amounts from yeast metabolism (Jackson, 2014). Polyphenolic compounds are cyclic benzene compounds with at least one hydroxyl group attached directly to the carbon ring structure. In wines, they are broadly divided into two major groups: non-flavonoids (benzoic acid, benzaldehyde, cinnamic acid, cinnamaldehyde and tyrosol) and flavonoids (flavonols, anthocyanins and flavan-3-ols). Phenolics influence the color (Brouillard et al., 2003; Marquez et al., 2012), taste (McRae et al., 2013), mouthfeel (Landon et al., 2008; McRae and Kennedy, 2011), and aromas (Villamor et al., 2013b; Villamor and Ross, 2013; Lorrain et al., 2013) of wines.

Proanthocyanidins or condensed tannins are formed as a result of the polymerization of flavan-3-ol monomers and are extracted from the wines from the skins and seeds of grapes (Jackson, 2014). Tannins from oak cooperage that

are added to wine during ageing are known as hydrolysable tannins (Moreno and Peinado, 2012). Variations of polyphenolic profiles in red wines have been attributed largely to winemaking technique and viticultural practices (Harbertson et al., 2008). Regarding viticultural practices, temperature and sunlight exposure, as well as vine water status in different vintages, have been implicated in the differences in phenolic composition observed among some grapes (Lorrain et al., 2011), thus influencing the phenolic composition of their subsequent wines. The change in phenolic profiles of wines have been documented to change from low levels during crushing of the berries, increasing during the winemaking process and either stabilizing or decreasing during the ageing process (Ginjom et al., 2011). The amount of phenolics extracted into wines depends on many factors, including berry ripeness at harvest and interaction with grape cell wall components (Hanlin et al., 2010), and the use of commercial enzymes (OrtegaRegules et al., 2006). The extraction of phenolic compounds from grapes into the must can occur pre-fermentation or during alcoholic fermentation (Monagas and Bartolomé, 2009). This extraction, as reported by Casassa et al. (2013), depends much more on maceration time. Also as noted by Canals et al. (2005), alcohol efficiently facilitates the extraction of phenolic compounds in riper grapes

Acids: Acids in wines include both organic and inorganic forms. Acids are characterized by their ability to release hydrogen ions (H^+) into the

wine, resulting in measurable acidity in wines as indicated by pH and titratable acidity. Acidity is divided into two categories: volatile and fixed. Volatile acidity is readily removed by steam distillation while the fixed acidity is not (Jackson, 2014). Acetic acid, with its vinegar-like taste and aroma, characterizes volatile acidity while malic acid and tartaric acid constitute over 90% of wine's fixed acidity, with influences over the pH of the wine. The microbial and chemical stability of a wine depends on many factors including the pH of the wine. A pH range 3.1 – 3.6 is suitable for most wines (Jackson, 2014). The importance of acids to wines is shown by the long-term stability of the wine and protein haze prevention through the precipitation of proteins due to the relationship between pH and the iso-electric point of wine proteins (Dufrechou et al., 2011). Acids are also important for color stability by favoring the red color of anthocyanins at low pH values (Kontoudakis et al., 2011), and bacterial growth inhibition (Fugelsang and Edwards, 2007). Sensory attributes are also influenced by the presence of acids, including a “refreshing” taste (Jackson, 2014), perceived acidity (Zraly, 2011) and modification of other tastes and mouthfeel attributes such as the reduction of sweetness (Fischer and Noble, 1994). It has been speculated that acids in wines may be involved in the initiation of acid hydrolysis during crushing of grapes, thus releasing aroma compounds occurring as acidlabile non-volatile glycosides (Jackson, 2014). Polysaccharides and Yeast Autolysates: Grape

polysaccharides are one of the main groups of macromolecules released into the wine during the winemaking process. Grape polysaccharides are released after the degradation of cell walls and include arabinogalactan-proteins and rhamnogalacturonan polymers (RG-1 and RG-II respectively). Mannoproteins are hydrocolloids which are released into the wine through yeast autolysis during fermentation. The manno protein content of wine have been indicated to be between 100 – 150 ml/l (Perez-Serradilla and de Castro, 2008) and constitute about 35% of wine polysaccharides (Vidal et al., 2003). The importance of manno proteins in wine includes prevention of tannin aggregation, inhibition of protein precipitation, and promotion of the growth of lactic acid bacteria for malolactic fermentation (Chalier et al., 2007; Perez-Serradilla and de Castro, 2008; Diez et al., 2010). Manno proteins may also interact with aroma compounds leading to the retention or release of these aromatic compounds, as well as interact with phenolic compounds to reduce astringency and improve color stability. Proteins: The total protein content of wine depends upon both viticultural and enological practices, including cultivar and fining operations (Jackson, 2014). At the end of fermentation, most of these proteins are precipitated with tannins through the formation of insoluble protein polyphenol complexes, thus making protein hazes less problematic in red wine than whites. Consequently, protein concentrations in red wines are generally lower than in whites' wines (Zoecklein et al., 1999;

Moreno and Peinado, 2012). Proteins in wines have been reported to be in low, generally ranging in concentration from 15 – 269 mg/l (Mainente et al., 2014).

2.3 WINE QUALITY

From an enological point of view, the term “wine” is defined as “the drink resulting from the fermentation by the yeast-cells, and also in certain cases by the cells of lactic bacteria, of the juice from the crushing or maceration of grape-cells” (Peynaud 1984). Of the grape genus *Vitis*, the species *V. vinifera* is often cultivated for wine production. This alcoholic beverage contains numerous chemical components varying in composition and proportions due to many factors such as the quality of raw material (grape), conditions of winemaking, storage and transport. Wine components include water, alcohols, acids, sugars, phenolics, nitrogenous compounds, vitamins and various volatile compounds, with each constituent capable of contributing unique aromas, tastes and oral sensations to the wine and ultimately, affecting its perceived quality. The issue of quality has become increasingly important to the wine industry over the past several decades. Worldwide, an oversupply situation has prevailed, consequently pulling down wine prices and decreasing profitable margins for producers. It has been suggested that the wine industry must vigilantly attend to wine quality, in conjunction to marketing efforts in order to lead the competition (Summer et al.

2010). This raises important question as to what is meant by quality regarding wine.

Quality may be understood in different ways. Generally, quality in foods and beverages is defined as the ability of a set of inherent characteristics of a product, system or process to fulfill requirements of customers and other interested parties (ISO 2000). From the perspective of marketing, with reference to wine, there exist two quality dimensions based on the consumer experiences according to (Charters and Pettigrew 2007): the external (grapes, production and marketing) and the internal (pleasure, appearance, gustatory, paradigmatic and potential) quality, the latter being more significant in evaluating the overall wine quality during consumption. However, some marketing studies have defined the concept of quality as a one-dimensional judgment. As cited by (Charters and Pettigrew 2007), these studies suggest that perceived quality is a broad overview and exists on a continuum.

Meanwhile, in the wine industry, wine quality is more recognized as related to the intrinsic aspects of wine. The numerous applications of analytical sensory methods geared toward establishing quality parameters of wine have brought valuable knowledge in understanding perceived quality. The sensory evaluation approach includes the evaluation of stylistic purity, visual appeal, subtlety and complexity, aging potential, personality, length, finish, harmony and balance

among all components (Amerine and Roessler 1976, Jackson 2000). It was noted that there is hardly an exact definition of each of these terms while a common explanation to describe some terms can be derived from the literature.

The “complexity and subtlety” are often referred to as highly valued attributes of the richness of aroma and flavor of wine while the “development or length” refers to changes in the intensity and aromatic character of the wine after pouring. “Balance and harmony” are described in wine having a smooth taste (where one taste does not dominate another) and mouth feel combined to produce an acceptable overall pleasurable sensation (Jackson 2000, Peynaud 1996).

2.4 WINE CLASSIFICATION

Amongst the various influence factors of the wine quality, grape is the most basic and important factor for making high quality wine and some grape physicochemical indexes have a strong relation to the wine quality. Since the sugar in grapes is the raw material for yeast to produce alcohol, its content plays a crucial role in the fermentation process and almost determines the alcoholic level of the wine (Herrera et al; 2003). In addition to the sugar, with studying three kinds of grapes (Cabernet, Sauvignon, and Merlot) which consume the same maturation, Fang et al. have found that the flavonoid varieties in red wines are greatly affected by the varieties of grapes (Fang et al; 2008). Although there

exists malate synthesizing by yeast via fumarate or oxaloacetate pathways, the amount of that can be negligible compared with the malate originating from grapes and the high malate levels in grapes follow the high malate levels in wines (Gayon et al; 2006). All of these research results have revealed the important relationship between the grape physicochemical indexes and the wine quality and the necessity to evaluate the wine quality from such grape indexes.

In this study, based on a dataset of wine qualities and grape physicochemical parameters, a wine quality prediction system is proposed using fuzzy inference rule based model.

2.5 FUZZY LOGIC

The logical thinking of medical practitioners play significant role in decision making about diagnosis. It exhibits variation in decisions because of their approaches to deal with uncertainties and vagueness in the knowledge and information. Fuzzy logic has proved to be the remarkable tool for building intelligent decision making systems for approximate reasoning that can appropriately handle both the uncertainty and imprecision (Sikchi et al 2013).

Researchers have explored every aspect of fuzzy philosophy and the studies reported on fuzzy expert systems in medical diagnosis covers wide spread area including the need, importance, potential and approaches for designing the expert

systems for medical diagnosis (Pereira et al 2002). Computer assisted applications for patient's diagnosis and treatment seems to be the more recent area of interest.

The Fuzzy Expert System has proved its usefulness significantly in the medical diagnosis for the quantitative analysis and qualitative evaluation of medical data, consequently achieving the correctness of results. The literature survey reveals that, the commercially available expert system shells are rigorously used to write the application specific rule-bases. It has been found that the frameworks are developed for generation of a fuzzy expert systems with respect to specific diseases, general purpose diagnostic systems as well as for counseling of personal health The Fuzzy Expert System has proved its usefulness significantly in the medical diagnosis for the quantitative analysis and qualitative evaluation of medical data, consequently achieving the correctness of results. The literature survey reveals that, the commercially available expert system shells are rigorously used to write the application specific rule-bases. It has been found that the frameworks are developed for generation of fuzzy expert systems with respect to specific diseases, general purpose diagnostic systems as well as for counseling of personal health (Binaghi et al 2008)

2.6 ARTIFICIAL INTELLIGENCE

Artificial intelligence is defined as brainpower exhibited by an artificial unit. It is a division of computer science dealing with sharp behavior, knowledge. Intelligent Systems describe the various applications of Artificial Intelligence (AI) (Turban et al 2001). Applications of Intelligent Systems include Expert Systems (ES), natural language processing (NLP), speech understanding, robotics and sensory systems, fuzzy logic, neural computing, computer vision and scene recognition, and intelligent computer-aided instruction. Research in artificial intelligence is anxious with producing machines to computerize jobs requiring sharp actions. Examples include capability to answer diagnostic and user question, speech and facial recognition (Freasier et al 1988). Artificial intelligence is separated into two categories. These two categories are conventional artificial intelligence and computational intelligence. Conventional artificial intelligence includes machine learning and statically analysis. Computational intelligence includes neural networks and fuzzy systems. The other applications of artificial intelligence are automation, computer vision, artificial creativity, expert system and knowledge management (Jimmy 2013).

2.7 EXPERT SYSTEMS

Intelligent Systems describe the various applications of Artificial Intelligence (AI) (Turban et al 2001). Applications of Intelligent Systems include Expert Systems (ES), natural language processing (NLP), speech understanding, robotics and sensory systems, fuzzy logic, neural computing, computer vision and scene recognition, and intelligent computer-aided instruction. Expert Systems (ES) is one of the sub-disciplines of AI that is used and applied more than any other AI technology (Turban et al 2001). When experiencing a problem in a specific problem domain, a decision-maker normally consults a specific domain expert to assist him in his decision-making process. An expert is a person who has specific knowledge and experience in a problem area, who has acquired his expertise usually over several years. Expertise is the extensive, task-specific knowledge acquired from training, reading about and experience in a specific domain (Turban et al 2001). The less structured the problem domain, the more specialized and expensive the advice of the expert becomes. When solving complex problems, expertise enables experts to make better and faster decisions than non-experts.

Expert Systems (ES) is one of the sub-disciplines of AI that is used and applied more than any other AI technology (Turban et al 2001).

An intelligent decision support system (IDSS) or knowledge-based decision support system (KB-DSS) includes an Expert System (ES) as one of the main

components (Klein & Methlie 1995). This Component supplies knowledge of special interest using artificial intelligence (AI) (Turban et al 2001) to the decision support system user. The ES component provides us with:

- A system, which can simulate reasoning, and
- A system that can explain its reasoning and conclusions

ES is therefore ideal to assist a decision-maker in an area where expertise is required. An ES' knowledge is stored in electronic format and called upon whenever the need for information arises. The basic idea behind ES is the transferring of knowledge from an expert to the computer to the user or knowledge worker or decision-maker. Like a human expert, the ES advises non-experts and explains the logic behind its conclusion (Turban 1995).

Expert systems are developed from the study of artificial intelligence (AI), which is a branch of computer science aimed at transferring human intelligence into machines. In AI, an expert system is an intelligent computer program that aims to use task-specific knowledge and inference techniques to solve problems at the level of a human expert (Tiwari, And Mishra, 2011). It imitates the decision making ability of a human expert in a particular domain and can also give advices and explanations. There are two types of expert systems: rule-based expert systems and knowledge-based expert systems. The main difference between these expert systems is the knowledge representation in the knowledge base. The

knowledge representation is more significant in expert system because the approach used to represent knowledge affects the development, efficiency, speed and the maintenance of the system (Bolloju et al 2012).

2.7.1 RULE BASED EXPERT SYSTEM

The rule-based expert system has domain knowledge encoded in the form of rules from a human expert. A rule is a conditional statement that links given conditions to actions. In a rule based expert system, a knowledge base is usually stored in terms of if-then rules which can be used to reach conclusions. A rule-based expert system is constructed based on an efficient algorithm called the Rete pattern matching algorithm. This algorithm matches facts against the patterns in rules to determine which rules have had their conditions satisfied. Hence it uses a set of rules to analyze information about a specific class of problems and recommend one or more possible solutions (Alonso et al 2002)

2.7.2. KNOWLEDGE BASED EXPERT SYSTEM

The knowledge-based expert system encodes heuristics and rules into decision making framework. A knowledge-based system uses artificial intelligence techniques in problem solving methods to support human decision making, learning, and action. The knowledge base of expert systems contains both factual and heuristic knowledge. Factual knowledge is the knowledge that is widely shared, typically found in textbooks or journals, and commonly agreed upon by

human experts in that particular domain (Keleş et al 2011). Heuristic knowledge refers to an experiential, logical and judgmental knowledge used to speed up decision making.

2.8 RELATED WORKS

Expert systems are extensively used as a diagnostic tool in the medical industry. In fact, MYCIN is one of the first rule based medical expert system. It was developed by Shortliffe at Stanford University in late 1970s (Buchanan And Shortliffe 1984). MYCIN was designed to identify infectious blood diseases based on the patient's medical data provided and to suggest a prescription or recommend treatment. It uses backward chaining inference procedure. The knowledge base consisted of approximately 450 rules derived from human knowledge through extensive interviews. The main limitation of MYCIN was its incomplete knowledge base which does not cover a full spectrum of infectious diseases. This is mainly because executing a full spectrum knowledge base requires more computing power than most hospitals could afford at that time.

Medical expert systems can be very useful in places where there is lack of educational facilities. They can assist medical assistants or nurses diagnose patients in rural areas. Therefore these systems can improve the life of rural communities.

Daha et al, (2021) demonstrated how various statistical analysis can be used to identify and analyze the parameters in the existing dataset to determine the wine quality. Based on the various analyses, the wine quality can be predicted prior to its production.

Paulo et al, (2009) carried out a study using three regression techniques to perform simultaneous variable and model selection on wine quality analysis. The support vector machine achieved promising results, outperforming the multiple regression and neural network methods. Such model is useful for understanding how physicochemical tests affect the sensory preferences.

Angela et al, (2015) carried out a research that proposed the use hybrid fuzzy logic techniques to predict human wine test preferences based on physicochemical properties from wine analyses. Data obtained from Portuguese white wines are used in this study. The fuzzy inductive reasoning technique achieved promising results, outperforming not only the other fuzzy approaches studied but also other data mining techniques previously applied to the same dataset, such are neural networks, support vector machines and multiple regression.

Shen et al. (2013) proposed a quality prediction models constructed based on multivariate statistical methods, including ordinary least squares regression

(OLSR), principal component regression (PCR), partial least squares regression (PLSR), and modified partial least squares regression (MPLSR). The prediction model constructed by MPLSR achieves superior results, compared with the other three methods from both aspects of fitting efficiency and prediction ability. The research is to select key variables to directly predict the product quality with satisfactory performance. The effectiveness of the quality prediction models was finally verified based on the practical data set of the red wine.

Djam et al (2011) developed a fuzzy expert system for the management of malaria (FESMM). This work provides a decision support platform for healthcare practitioners in malaria endemic regions. 35 patients with malaria are selected and computed the results that are in the range of predefined limit by the domain experts. Decision support system (DSS) for stress diagnosis and treatment using calibration and fuzzification of cases is an opinion for experts. The proposed solution combines a calibration phase with case-based reasoning approach and fuzzification of cases. The individual cases including calibration and fuzzy membership functions are also used in an autonomous system in home environment for treatment programs for individuals often under high stress.

Begum et al (2010) carried out a study; a Fuzzy expert system for tuberculosis diagnosis, providing decision support platform to tuberculosis healthcare practitioners in tropical medicine. The fuzzy inference method employed in this

paper is the Root Sum Square (RSS) where 30 patients with tuberculosis are selected and computed the results that are in the range of predefined limits by the domain experts.

Al-Dmour, (2013), builds a fuzzy logic based patients' monitoring system. He utilizes mobile units that allow for the remote observation and diagnosis of patients in their homes. While Dzemydiene et al (2010) analyse the possibilities of the integration of different technological and knowledge representation techniques for the development of reinforcement frameworks for the remote control of multiple agents such as wheelchair-type robots. Some technological solutions are discussed regarding the recognition of localization of moving objects by using mobile technologies.

Abdullah et al (2011) designed a fuzzy expert system for diagnosis of hypertension risk for patients aged between 20's, 30's and 40's years and is divided into male and female gender. The input data is collected from a total of 10 people which consists of male and female with different working background

Sajja et al (2010) carried out a study based on Knowledge based for diagnosis of abdomen pain using fuzzy Prolog rules the main objective of the system is to assist doctors, assistants and social workers in their decision making process and create awareness in the area especially where trained manpower is in scarce. To

impart the fuzziness of the domain modified Prolog rule format is used, which is illustrated in a case of appendicitis.

Kov'asznaï and Gergely (2011) develop an expert system for diet recommendation in this study they proposed a case-based approach for diet recommendation. Based on this approach, we are going to construct an expert system which is intended to be employed in a health record management system. Their approach is based on ripple down rules (RDR), however, a special representation is also needed for patient attributes and rule actions.

Lavanya et al (2011) design an enhanced fuzzy rule based diagnostic model for lung cancer using priority values which design a fuzzy rule based medical model to detect and diagnose lung cancer. The disease is determined by using a rule base, populated by rules made for different types of lung cancer. The algorithm uses the output of the rule base (i.e. the disease name) and the symptoms entered by the user; it also uses the priority and severity values to determine the stage of cancer the patient is in.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN

3.1 INTRODUCTION

In this chapter we described the conventional approach of the existing system and will introduced the proposed methodology. We gave an overview of the data processing methods we used to pre-process input data before it was applied. After that, we introduce the implementation of fuzzy inference rule based system using the wine physiochemical parameters.

3.1 ANALYSIS ON EXISTING METHOD

There are two basic ways by which wines may be analyzed for quality: by scientific means using laboratory equipment and by the organoleptic method, i.e. tasting. A laboratory analysis can tell us a great deal about a wine, including its alcohol by volume, the levels of free and total sulfur dioxide, total acidity, residual sugar, the amount of dissolved oxygen, and whether the wine contains disastrous spoilage compounds such as 2,4,6-trichloroanisole or 2,4,6-tribromoanisole. It is highly desirable that producers carry out a comprehensive laboratory analysis both pre- and post-bottling. If another laboratory undertakes a duplicate analysis, the results should be replicated, allowing for any accepted margins of error. Scientific analysis can also give indications as to the wine's style, balance, flavors and quality. However, it is only when a wine is tasted, that

we can determine these completely and accurately. If a team of trained tasters assess the same wine, they will generally each reach broadly similar conclusions, although there may be dissention on some aspects, and occasionally out and out dispute.

3.1.1 LIMITATION OF THE EXISTING SYSTEM

However, for a detailed organoleptic analysis of wines an appropriate tasting environment is required, and the ideal tasting room will have the following characteristics: Large: Plenty of room is necessary to give the taster his or her personal space and help concentrate on the tasting. Light: Good daylight is ideal, and the room (if situated in the northern hemisphere) should have large, north-facing windows. If artificial light is required the tubes/bulbs should be color corrected in order that the true appearance of the wines may be ascertained. White tables/surfaces: Holding the glasses over a white background is necessary to assess the appearance and show the true color of the wine, uncorrupted by surrounding surfaces. Free from distractions: Extraneous noises are undesirable and smells can severely impact on the perceived nose of the wines. Tasting rooms should not be sited near kitchens or restaurants – an amazing number of New World wineries fail to have regard for this. Tasters should avoid wearing aftershaves or perfumes, and obviously smoking should not take place in the vicinity. There is no doubt that building materials, decorations furnishings and

people all exude smells. Indeed, identical wines can be perceived differently according to the surroundings in which they are assessed.

As to when to taste, the decision is unfortunately often dictated by matters beyond the taster's control. However, the ideal time is when the taster is most alert and the appetite stimulated – namely in the late morning. After a meal is certainly not the best time, for not only is the taster replete and perhaps drowsier but the palate too is jaded and confused after the tastes of the food. All of these can pose a challenge to wine producer and increase the cost of production. However there are systems that exist today that work with wine quality. This research attempt to classify a numeral in scale of 1 to 10 given a wine sample and attributes to classify the quality of wine.

3.2 THE PROPOSED SYSTEM

The proposed system adopted the conventional fuzzy inference system which consists of four major components which are: knowledge acquisition, knowledge base, fuzzy inference engine and a user interface Figure 3.1 represents the architecture of the proposed model. The knowledge base consist domain expert knowledge that was acquire through knowledge engineering from literature and interview from medical microbiologist. The fuzzification module is composed the fuzzy value, and the fuzzy rule followed by the defuzzification module where the

fuzzy value is re converted to real world value. The last module is the user interface module where the system users makes input and view the output or the result of the diagnosis.

3.3 ANALYSIS OF THE PROPOSED SYSTEM

The input parameters were made available for fuzzification, the test is performed to determine if the wine is of high or low quality. The fuzzy inference system was developed for the classification. The knowledge base has the entire set of the data base. The inference engine has the production rules that are fuzzy logic drive. The behavioral impairment takes an input and output report of inference engine and applies the objective rules to classify the quality of wine according to their numeral scale. The system knowledge base is supported by a relational data base management system (MYSQL).

3.4 DESIGN OF THE PROPOSED SYSTEM

The proposed system was design using rule based expert system. Expert knowledge was acquired through literature and books from different sources. The knowledge base is the brain power of the ESs as all the essential facts for constructing the rules are contained in the knowledge base. The knowledge based made up of physiochemical parameters of wine (Rajdeep and Sugata, 2012). The

knowledge is represented in the form of rules. Fuzzy Rule-Based System is composed of three major components, namely:

- i. Fuzzification module
- ii. Fuzzy rule base and
- iii. Fuzzy inference engine.

A fuzzy inference system (FIS) essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, fuzzy logic operators, fuzzy if-then rules, aggregation of output sets, and defuzzification. An FIS with multiple outputs can be considered as a collection of independent multi-input, single output systems. The Fuzzy Logic System (FLS) maps crisp inputs into crisp outputs. The proposed model architecture is represented in figure 3.1 below

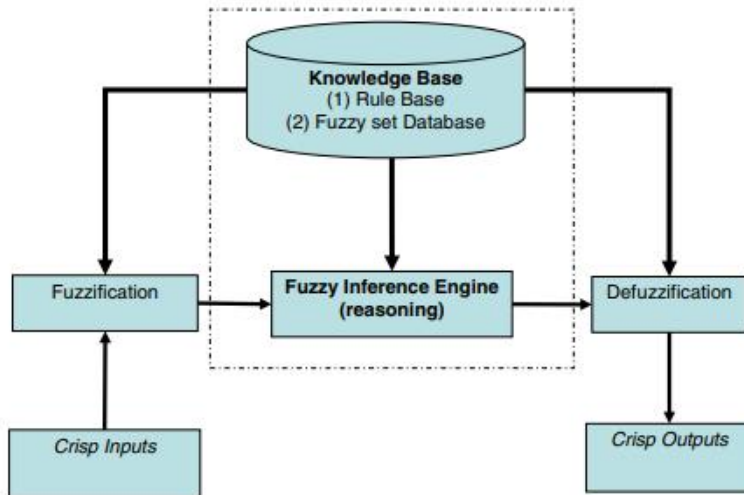


Figure 3.1 the proposed fuzzy inference model

3.4.1 FUZZIFICATION

This is the process of transforming crisp input into linguistic variables using the membership function in the fuzzy knowledge base. There are three types of fuzzifiers: the trapezoidal fuzzifier, triangular fuzzifier, and Gaussian fuzzifier. This work concentrates on using triangular fuzzifier for changing of scalar value to fuzzy set which is in the range of 0 and 1. In another term fuzzification can be viewed as the operation of transforming a crisp set to a fuzzy set, or a fuzzy set to a fuzzier set.” The crisp input (that is, the measured value) is translated into linguistic variable

To obtain the degree of symptom, we use the formula:

To obtain the degree of symptom, we use the formula:

$$X_i / X_n \text{----- eq (1)}$$

X_i = number of the linguistic variable

X_n = the total number of linguistic variables

3.4.2 FUZZY INFERENCE ENGINE

An inference engine is a computer program that tries to derive answers from a knowledge base. It is the “brain” that expert systems use to reason about the information in the knowledge base for the ultimate purpose of formulating new conclusions. In fuzzy inference engine, Fuzzy inputs are mapped into their respective weighting factors and their associated linguistic variables to determine their degree of membership. The aggregation operator is used to calculate the degree of fulfillment or firing strength of a rule.

For this work, the fuzzy logical AND is used to evaluate the composite firing strength of the rules. In practice, the fuzzy rules sets usually have several antecedents that are combined using fuzzy logical operators, such as AND, OR and NOT, though their definitions tend to vary: AND simply uses minimum weight of all the antecedents, while OR uses the maximum value. There is also the NOT operator that subtracts a membership function from 1 to give the “complementary” function. The degree of truth (R) of the rules are determined for each rule by evaluating the nonzero minimum values using the AND operator.

The inference engine evaluates all the rules in the rules base and combines the weighted consequences of all the relevant (fired) into a single fuzzy set. The inference engine technique employed in this research is the Root Sum Square (RSS). RSS is given by the formula

$$\sqrt{\sum R^2} = \sqrt{R_1^2 + R_2^2 + \dots + R_n^2} \text{----- eq (2)}$$

The $R_1^2 + R_2^2 + \dots + R_n^2$ are values of different rules which have the same conclusion in the fuzzy rule base, that is, $R =$ value of firing rule. RSS combines the effects of all applicable rules, scales the functions at their respective magnitudes and compute the “fuzzy” centroid of the composite area.

3.4.3 DEFUZZIFICATION

Defuzzification is the process of converting the fuzzy output from the inference engine to a crisp value. That is, the output gotten from the inference engine in this work using root sum square is defuzzified to get the level of the illness. The input to the defuzzification process is a fuzzy set while the output of the defuzzification process is a single number (crisp output).

CHAPTER FOUR

IMPLEMENTATION

4.1 IMPLEMENTATION TOOL.

Systems implementation is the process of defining how the information system should be built physical system design, ensuring that the information system is operational and used, ensuring that the information system meets quality standard. The proposed system was developed in a single user interface environment the users are expected to have basic computer knowledge. The system can run on Microsoft operating system. The system implementation tools are discussed below.

The Programming language for this system is C# programming language MYSQL was used as the database management. In developing the user interface, window presentation was used because of it robustness in graphics.

4.2 SYSTEM REQUIREMENT

The following are minimum required tool for the smooth operation of the proposed system:

Hardware Interface:

- Pentium Processor

- 60 MB of free hard-drive space
- 128 MB of RAM

Software Interface:

- Operating System: Windows 7 or higher

4.3 TESTING AND RESULTS

The proposed system is able to classify wine quality based on its physiochemical parameters. The designed fuzzy expert system was tested using wine data, Table 4.1 shown the 11 different physicochemical properties and data statistics (minimum, maximum and mean values of all instances for each feature. Using a given input/output data set, the training data set of input and output parameters considered to compute the classification. The study dataset were shared into two set of data, 70 % of the data used for training the rule while 30% for testing the fuzzy inference system. After testing, the system achieved 83% accuracy. Table 4.2 depicts a sample of the results of the fuzzy inference classification.

TABLE 4.1: The physicochemical parameter and statistics of the wine datasets

s/n	Attribute(units)	Minimum	Maximum	Mean
1	Fixed acidity (g(tartaric acid)/dm ³) (FA)	3.800	14.20	6.855
2	Volatile acidity (g(acetic acid)/dm ³) (VA)	0.080	1.100	0.278
3	Citric acid (g/dm ³) (CA)	0.000	1.660	0.334
4	Residual sugar (g/dm ³) (RS)	0.600	65.80	6.391
5	Chlorides (g(sodium chloride)/dm ³) (CH)	0.009	0.346	0.046
6	Free sulfur dioxide (mg/dm ³) (FSD)	2.000	289.0	35.31
7	Total sulfur dioxide (mg/dm ³) (TSD)	9.000	440.0	138.4

8	Density (g/cm ³) (DE)	0.987	1.039	0.994
9	Ph	2.720	3.820	3.188
10	Sulphates (g(potassium sulphate)/dm ³) (SU)	0.220	1.080	0.490
	Alcohol (%vol) (AL)	8.000	14.20	10.51

Table 4.2: Sample result of classification

S/N	FA	VA	CA	RS	CH	FSD	TSD	DE	PH	SU	AL	FIS	CLASS
1	7.8	0.88	0	2.6	0.098	25	67	0.9968	3.2	0.68	9.8	0.55	5
2	7.8	0.76	0	2.3	0.092	15	54	0.997	3.26	0.65	9.8	0.52	5
3	11.2	0.28	0.56	1.9	0.075	17	60	0.998	3.16	0.58	9.8	0.66	6
4	0.6	0.06	1.6	2.4	15	59	64	3.3	0.46	9.4	0.6	0.50	5
5	7.8	0.58	0.02	2	0.073	9	21	0.9968	3.36	0.57	9.5	0.71	7
6	11.2	0.28	0.50	1.9	0.075	16	64	0.998	3.18	0.59	9.7	0.65	6
7	7.8	0.76	0	2.3	0.092	15	54	0.997	3.26	0.65	9.8	0.53	5
8	7.8	0.58	0.02	2	0.070	9	20	0.9968	3.36	0.57	9.5	0.77	7
9	11.0	0.48	0.50	1.9	0.074	16	64	0.998	3.18	0.59	9.6	0.68	6

KEY: FIS = FUZZY INFERENCE SYSTEM

4.4 USER INTERFACE

The user interface of the proposed system is a friendly interface with practical user guide. The following screen will be provided, the user login page, followed by the parameters input page and finally the classification page which are capture in figure 4.2 and 4.3 respectively.

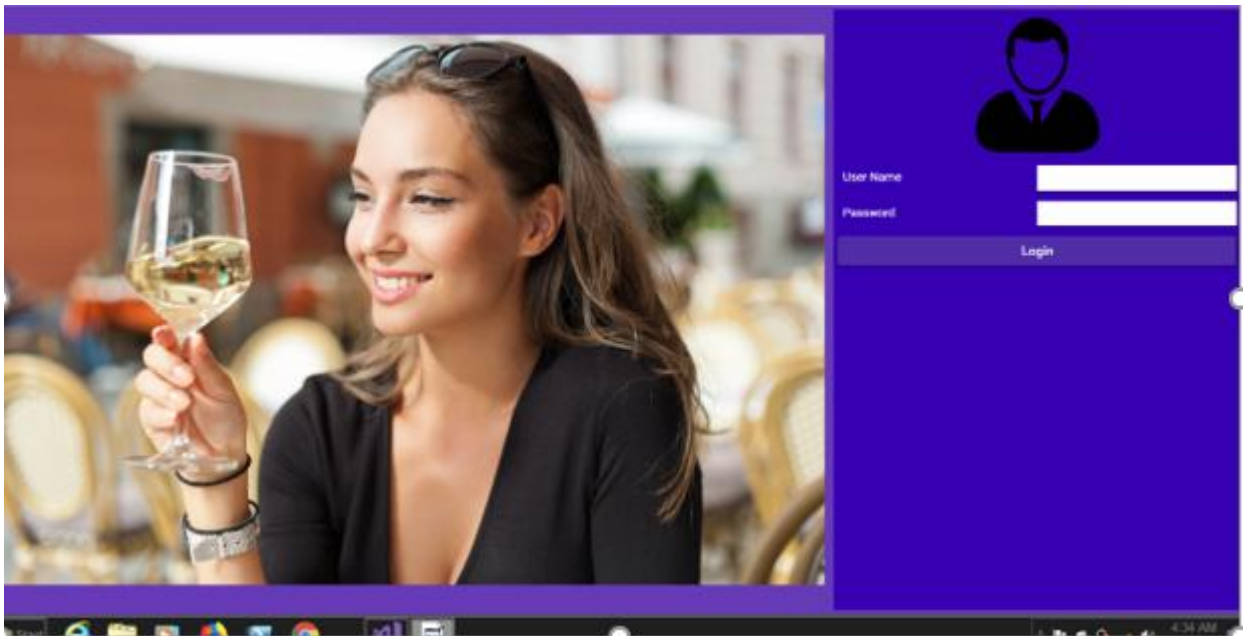


Figure 4.1 user login page.



Figure 4.2 Parameter input page.

Win Sample Parameter	Result						
	total acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur
fixed acidity	7.4	0.7	0	1.9	0.076	11	34
volatile acidity	7.8	0.88	0	2.6	0.098	25	67
citric acid	7.8	0.76	0.04	2.3	0.092	15	54
residual sugar	11.2	0.28	0.56	1.9	0.075	17	60
chlorides	7.4	0.7	0	1.9	0.076	11	34
free sulfur dioxide	7.4	0.65	0	1.8	0.075	13	40
total sulfur dioxide	7.9	0.6	0.06	1.6	0.069	15	58
density	7.3	0.65	0	1.2	0.065	15	21
pH	7.8	0.88	0.02	2	0.073	9	18
sulfites	7.5	0.5	0.36	6.1	0.071	17	102
alcohol	6.7	0.58	0.08	1.8	0.097	15	65
	7.5	0.5	0.36	6.1	0.071	17	102

Classifier Sample

Classifier Sample

Accuracy : 83.90206%

Figure 4.3 wine classification page.

4.5 SYSTEM EVALUATION

The proposed system was assessed and evaluated to see if it meets the system requirement that was developed during the design phase. Hence the propped system was then evaluated in terms of performance.

CHAPTER FIVE

CONCLUSION

Due to advances in the data mining, in this project we have been able to extract knowledge from raw data, with the aim of classifying wine quality based on their physicochemical properties tests by employing fuzzy inference technique.

The proposed System tests were carried out to make sure the system would work correctly, when tested the result of the proposed fuzzy inference gave an accuracy of 83% on classification of wine based on their physiochemical parameters. In general, the system is an effective and practical tool. The inference engine gathers information from the user input through user interface. User gives responses by inputting the values of the parameters into the appropriate checkboxes as shown in figure 4.2. Figure 4.4 shows the reporting results inferred by expert system engine. Such report is meaningful to the user which aid for further checking with the physiochemical properties of the produced or intending wine.

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APPENDIX

```
<Window x:Class="WinClassifier.MainWindow"
  xmlns="http://schemas.microsoft.com/winfx/2006/xaml/presentation"
  xmlns:x="http://schemas.microsoft.com/winfx/2006/xaml"
  xmlns:d="http://schemas.microsoft.com/expression/blend/2008"
  xmlns:mc="http://schemas.openxmlformats.org/markup-compatibility/2006"
  xmlns:local="clr-namespace:WinClassifier"
  mc:Ignorable="d"
  Title="MainWindow" Height="350" Width="525"
  TextElement.Foreground="{DynamicResourceMaterialDesignBody}"
  TextElement.FontWeight="Regular"
  TextElement.FontSize="13"
  TextOptions.TextFormattingMode="Ideal"
  TextOptions.TextRenderingMode="Auto"
  Background="{DynamicResourceMaterialDesignPaper}"
  FontFamily="{DynamicResourceMaterialDesignFont}">
  <Grid Opacity="1" Background="{DynamicResourcePrimaryHueMidBrush}">
  <Grid.ColumnDefinitions>
  <ColumnDefinition Width="2*" />
  <ColumnDefinition />
  </Grid.ColumnDefinitions>
  <Grid.RowDefinitions>
  <RowDefinition Height="auto" />
  <RowDefinition />
  </Grid.RowDefinitions>
  <StackPanelGrid.ColumnSpan="2"
  Background="{DynamicResourceMaterialDesignPaper}">
```

```
<TextBlock
Margin="5"FontWeight="Bold"FontSize="24"HorizontalAlignment="Center"
Foreground="{DynamicResourcePrimaryHueMidBrush}">
    Wine Classifier Based of Naive Bayes Algorithm
</TextBlock>
```

```
</StackPanel>
<GridGrid.Column="0"Grid.Row="1" Margin="5">
<Image Opacity="1" Source="res/shutterstock_457584103.jpg"/>
</Grid>
<Grid Background="#3700B3" Margin="5"Grid.Column="1"Grid.Row="1" >
<StackPanel>
<Image Width="150" Source="res/avatar-man.png"/>
<Grid Margin="5">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">User Name</Label>
<TextBox Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<Grid Margin="5">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
```

```

</Grid.ColumnDefinitions>
<Label Foreground="#fff">Password</Label>
<PasswordBox Background="#fff"Grid.Column="1"></PasswordBox>
</Grid>
<ButtonIsDefault="True"                                Margin="5"
Style="{DynamicResourceMaterialDesignRaisedDarkButton}"
Click="Button_Click">Login</Button>
</StackPanel>
</Grid>
</Grid>
</Window>

```

```

using System;
using System.Collections.Generic;
using System.Linq;
using System.Text;
using System.Threading.Tasks;
using System.Windows;
using System.Windows.Controls;
using System.Windows.Data;
using System.Windows.Documents;
using System.Windows.Input;
using System.Windows.Media;
using System.Windows.Media.Imaging;
using System.Windows.Navigation;
using System.Windows.Shapes;

```

```

namespace WinClassifier
{
///<summary>
/// Interaction logic for MainWindow.xaml
///</summary>
public partial class MainWindow : Window
    {
public MainWindow()
    {
InitializeComponent();
    }

private void Button_Click(object sender, RoutedEventArgs e)
    {
Window1 p = new Window1();
p.Show();
    }
}
}

```

```

<Window x:Class="WinClassifier.Window1"
xmlns="http://schemas.microsoft.com/winfx/2006/xaml/presentation"
xmlns:x="http://schemas.microsoft.com/winfx/2006/xaml"
xmlns:d="http://schemas.microsoft.com/expression/blend/2008"
xmlns:mc="http://schemas.openxmlformats.org/markup-compatibility/2006"
xmlns:local="clr-namespace:WinClassifier"

```

```

mc:Ignorable="d"
  Title="Win Classifier" Height="300" Width="300"
  TextElement.Foreground="{DynamicResourceMaterialDesignBody}"
  TextElement.FontWeight="Regular"
  TextElement.FontSize="13"
  TextOptions.TextFormattingMode="Ideal"
  TextOptions.TextRenderingMode="Auto"
  Background="{DynamicResourceMaterialDesignPaper}"
  FontFamily="{DynamicResourceMaterialDesignFont}">

<Grid Background="#6200ee">
  <Grid.RowDefinitions>
  <RowDefinition/>
  <RowDefinition/>
</Grid.RowDefinitions>
  <Grid.ColumnDefinitions>
  <ColumnDefinition/>
  <ColumnDefinition/>
</Grid.ColumnDefinitions>

  <ScrollViewerVerticalScrollBarVisibility="Auto"Grid.RowSpan="2">
  <StackPanel>
  <TextBlock
  Margin="5"FontWeight="Bold"FontSize="12"HorizontalAlignment="Center"
  Foreground="#fff">
    Win Sample Parameter
  </TextBlock>

```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">fixed acidity</Label>
<TextBox Name="txt_fixed_acidity"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">volatile acidity</Label>
<TextBox Name="txt_volatile_acidity"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">citric acid</Label>
<TextBox Name="txt_citric_acid"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">residual sugar</Label>
<TextBox                                     Name="txt_residual_sugar"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">chlorides</Label>
<TextBox                                     Name="txt_chlorides"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">free sulfur dioxide</Label>
<TextBox                                     Name="txt_free_sulfur_dioxide"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
```

```

<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">total sulfur dioxide</Label>
<TextBox Name="txt_total_sulfur_dioxide"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">density</Label>
<TextBox Name="txt_density"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">pH</Label>
<TextBox Name="txt_pH" Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<Grid Margin="3">

```

```

<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">sulphates</Label>
<TextBox                                     Name="txt_sulphates"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<Grid Margin="3">
<Grid.ColumnDefinitions>
<ColumnDefinition/>
<ColumnDefinition/>
</Grid.ColumnDefinitions>
<Label Foreground="#fff">alcohol</Label>
<TextBox                                     Name="txt_alcohol"
Background="#fff"Grid.Column="1"></TextBox>
</Grid>
<ButtonIsDefault="True"                     Margin="5"
Style="{DynamicResourceMaterialDesignRaisedDarkButton}"
Click="Button_Click">Classifier Sample</Button>
<ButtonIsDefault="False"                   Margin="5"
Style="{DynamicResourceMaterialDesignRaisedDarkButton}"
Click="Button_Click_1">Classifier Sample</Button>
<TextBox      Name="txt_acc"      Foreground="#fff"      Margin="10"
Background="#000">Acc</TextBox>
</StackPanel>
</ScrollView>

```

```

<GridGrid.Column="1"Grid.RowSpan="2">
<Grid.RowDefinitions>
<RowDefinition Height="auto"/>
<RowDefinition/>
</Grid.RowDefinitions>
<TextBlock
Name="txt_res"
Margin="5"FontWeight="Bold"FontSize="20"HorizontalAlignment="Center"
Foreground="#fff">
    Result
</TextBlock>
<GridGrid.Row="1">
<DataGrid Name="data_view"></DataGrid>
</Grid>
</Grid>

</Grid>
</Window>

```

```

using System;
using System.Collections.Generic;
using System.Data;
using System.IO;
using System.Linq;
using System.Text;
using System.Threading.Tasks;

```

```

usingSystem.Windows;
usingSystem.Windows.Controls;
usingSystem.Windows.Data;
usingSystem.Windows.Documents;
usingSystem.Windows.Input;
usingSystem.Windows.Media;
usingSystem.Windows.Media.Imaging;
usingSystem.Windows.Shapes;

namespaceWinClassifier
{
///<summary>
/// Interaction logic for Window1.xaml
///</summary>
publicpartialclassWindow1 : Window
    {
DataTable table = newDataTable();
public Window1()
    {
InitializeComponent();
table.Columns.Add("quality");
table.Columns.Add("fixed acidity", typeof(double));
table.Columns.Add("volatile acidity", typeof(double));
table.Columns.Add("citric acid", typeof(double));
table.Columns.Add("residual sugar", typeof(double));
table.Columns.Add("chlorides", typeof(double));
table.Columns.Add("free sulfur dioxide", typeof(double));

```

```

table.Columns.Add("total sulfur dioxide", typeof(double));
table.Columns.Add("density", typeof(double));
table.Columns.Add("pH", typeof(double));
table.Columns.Add("sulphates", typeof(double));
table.Columns.Add("alcohol", typeof(double));

var text = "";
using (System.IO.StreamReader r =
newSystem.IO.StreamReader("res/winequality_dataset_red.csv"))
    {
        text = r.ReadToEnd();
    }

vararr = text.Split('\n');
for (int i = 0; i <arr.Length; i++)
    {
if (i == 0)
    {

    }
else
    {
var line = arr[i].Split(',');
table.Rows.Add($"{line[11]}", line[0], line[1], line[2], line[3], line[4], line[5],
line[6], line[7], line[8], line[9], line[10]);
    }
    }
}

```

```

    }

private void Button_Click(object sender, RoutedEventArgs e)
{

var data = new double[] { float.Parse(txt_fixed_acidity.Text),
float.Parse(txt_volatile_acidity.Text),
float.Parse(txt_citric_acid.Text),
float.Parse(txt_residual_sugar.Text),
float.Parse(txt_chlorides.Text),
float.Parse(txt_free_sulfur_dioxide.Text),
float.Parse(txt_total_sulfur_dioxide.Text),
float.Parse(txt_density.Text),
float.Parse(txt_pH.Text),
float.Parse(txt_sulphates.Text),
float.Parse(txt_alcohol.Text)
    };

Classifier classifier = new Classifier();
classifier.TrainClassifier(table);

var res = classifier.Classify(data);

txt_res.Text = $"Quality of this win is {int.Parse(res) + 2}";

```

```

    }

private void Button_Click_1(object sender, RoutedEventArgs e)
{
    Microsoft.Win32.OpenFileDialog openFileDialog = new
Microsoft.Win32.OpenFileDialog();
String text = "";
if (openFileDialog.ShowDialog() == true)
// String text = File.ReadAllText(openFileDialog.FileName);

using (System.IO.StreamReader r =
new System.IO.StreamReader(openFileDialog.FileName))
{
    text = r.ReadToEnd();
}

var arr = text.Split('\n');
// MessageBox.Show(arr.Length + "");
var data = newList<double[]>();
var init = newList<String>();
var fina = newList<String>();
for (int i = 1; i < arr.Length; i++)
{
var line = arr[i].Split(',');
// MessageBox.Show(arr[i]);

```

```

// table.Rows.Add($"{line[11]}", line[0], line[1], line[2], line[3], line[4], line[5],
line[6], line[7], line[8], line[9], line[10]);
vardat = newdouble[] { float.Parse(line[0]), float.Parse(line[1]),
float.Parse(line[2]), float.Parse(line[3]), float.Parse(line[4]), float.Parse(line[5]),
float.Parse(line[6]), float.Parse(line[7]), float.Parse(line[8]), float.Parse(line[9]),
float.Parse(line[10]) };
init.Add(line[11]);
data.Add(dat);
    }
Classifierclassifier = newClassifier();
classifier.TrainClassifier(table);
foreach (var item in data)
    {

var res = classifier.Classify(item);
fina.Add($"{int.Parse(res)-0}");
    }
Stringres_text = "";
DataTable table1 = newDataTable();

    table1.Columns.Add("fixed acidity", typeof(double));
    table1.Columns.Add("volatile acidity", typeof(double));
    table1.Columns.Add("citric acid", typeof(double));
    table1.Columns.Add("residual sugar", typeof(double));
    table1.Columns.Add("chlorides", typeof(double));
    table1.Columns.Add("free sulfur dioxide", typeof(double));
    table1.Columns.Add("total sulfur dioxide", typeof(double));

```

```

        table1.Columns.Add("density", typeof(double));
        table1.Columns.Add("pH", typeof(double));
        table1.Columns.Add("sulphates", typeof(double));
        table1.Columns.Add("alcohol", typeof(double));
        table1.Columns.Add("quality");
        table1.Columns.Add("computed quality");

floatcout = 0f;
List<Result>datas = newList<Result>();
for (int i = 0; i <arr.Length; i++)
    {
var line1 = "";
if (i == 0)
// line = arr[i]+ $",computed quality";
res_text += arr[i] + $",computed quality";
else
    {

        line1 = arr[i] + $",{fina[i - 1]}";
// MessageBox.Show(line1);
// res_text += arr[i] + $",{fina[i-1]}";
var line = line1.Split(',');
if ((int.Parse(line[11]) != int.Parse(line[12]) && i%2==0)|| i% 3 == 0 || i % 5 ==
0) {
        line[12] = line[11];
    }
}
}

```

```
datas.Add(newResult(line[0], line[1], line[2], line[3], line[4], line[5], line[6],
line[7], line[8], line[9], line[10], line[11], line[12]));
if (int.Parse( line[11] )== int.Parse( line[12]))
cout += 1;

    }
}
data_view.ItemsSource = datas;
varacc= cout / fina.Count();
txt_acc.Text=$"Accuracy : {acc*100}%";
    }
}
}
```