EASTERN INTERNATIONAL UNIVERSITY

BECAMEX BUSINESS SCHOOL

Course: SCLM449 - Process Control And Improvement

MILK QUALITY MANAGEMENT

HAPPY COW LTD

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TABLE OF CONTETS

LIST OF FIGURES

LIST OF TABLES

I. Executive summary

1. Briefly summarize the context

Market context in Binh Duong with a developed economy, large population, large labor force and increasingly improving living standards combined with a clearly increasing trend of consuming milk, fresh milk, and high quality milk in Vietnam. This creates a real opportunity for Happy Cow Ltd if the company decides to expand into the province.

However, to take advantage of opportunities and explore potential market segments, Happy Cow Ltd needs to build a comprehensive strategy: ensuring high product quality, stable control throughout the entire production chain, establishing an effective distribution system, and building a reputable brand, to meet the high expectations of consumers in Binh Duong.If done well, the Binh Duong market can become a key consumption channel, helping Happy Cow Ltd build a strong brand in the premium and high-quality milk segment in the Southeast region.

2. Key findings on current milk quality

The current assessment shows that the production process is in a state of severe instability, with many significant deviations from expected operating standards.

2.1. Quality imbalance

About 40.51% of current manufacturing is classed as low quality, considerably over the permissible limit of the target market. This ratio reflects systemic inefficiencies and shows that current quality assurance mechanisms are not working consistently or are not strong enough.This data indicates the urgent need to streamline production processes and increase compliance with quality control requirements.

2.2. Root causes of instability

Analysis shows that temperature is the factor that most strongly affects product quality, with a correlation coefficient r = -0.42. This negative correlation shows that temperature fluctuations have a clear negative impact on production results. Large temperature fluctuations, from 34°C to 90°C, reflect serious problems in process control. The cause may come from unstable monitoring equipment, inaccurate control systems or non-compliance with standard operating procedures. Corrective measures should be implemented immediately to restore temperature stability and ensure consistency of the manufacturing process.

2.3. Defects in input and cleaning stages

The presence of foul odors and inconsistent turbidity indicate serious problems in input quality management.These symptoms suggest fluctuations in raw milk quality or errors in storage and initial handling, indicating systemic flaws in hygiene control, filtration efficiency and cold chain management before processing. These challenges not only directly influence product quality, but also damage brand reputation and consumer confidence. Therefore, it is necessary to strengthen cleaning processes, control of incoming materials and increase monitoring to ensure the long-term integrity of the production process.

3. Most important recommendations for continuous improvement

3.1. Strengthen process management and monitoring

To overcome the current instability, it is necessary to implement an Integrated Quality Management System, which allows continuous monitoring of important variables in the production process. This system should be established based on data-driven management principles, helping to detect early signs of deviation and react promptly before serious errors occur.

Moreover, management process personnel training must be aimed at developing analytical and real data-based decisions. Standardization of engineering, quality, and operations within the internal communication process, and periodic feedback are required.

3.2. Application of predictive modeling in quality control

The use of predictive models in quality supervision and control entails the construction and use of a Predictive Quality Model based on available data on temperature, turbidity, smell, and other operational parameters. The model can use regression, or machine learning, to determine the relationship that exists between the predictor variables and the quality of the output. A well-functioning forecasting system is capable of:

- Identifying trends of deviation early in the production cycle to prevent failure in the product.

- Optimizing the control of production conditions particularly temperature to reduce variability and boost the production of acceptable quality products.
- Real time control of quality to generate automated alerts and facilitate active management. Predict and control of quality to generate alerts and facilitate active control of quality.

3.3. Data integration and continuous improvement

Data from the entire production chain from fresh milk receipt, heat treatment, to packaging which needs to be integrated into a centralized data platform. This allows for trend analysis and continuous improvement, while also providing a foundation for long-term performance assessment.

II. Introduction

1. Background

The firm HAPPY COW Ltd. is taking a huge risk by laying down a highly competitive market expansion strategy in the Middle-earth region, starting with Binh Duong, which is a high-end consumer market that not only wants premium products but also expects top-notch reliability and consistency. However, the current production data points to a major inconsistency in the process as a polarization phenomenon is occurring, where both very high- and very low-quality products are being produced at the same time. This situation could lead to harm for the brand, rejection of the product by consumers, and declining trust - particularly in the case of very sensitive and high-value markets. Moreover, it is now or never for the Quality Management Team to change the company's quality assurance system from a reactive testing model to a proactive process control approach, which will stabilize the behavior of the process, eliminate uncontrolled variation, and ensure that the quality of the product is up to the expectations of the market.

2. Report Objectives

The report is centered on two principal goals, which are directly related to the two questions presented and at the same time are in line with HAPPY COW's strategic development plans. The first goal is to analyze the production system's attributes of stability, predictability, and capability by means of statistical indicators such as Cp, Cpk, Pp, and Ppk, thus performing an evaluation of the current process performance. In addition to this analysis, the distribution characteristics of the key quality parameters will be examined to verify the existence of a polarization effect and to find out which process variables such as Taste, Odor, Turbidity, Temperature, and other manufacturing-related factors have the most detrimental and strongest impact on the final Quality Grade. By identifying these variables that have an effect, the company will be able to very precisely locate the primary causes of variability that lead to the inconsistent product outcomes.

The second goal is to recommend a thorough plan for process management and control aimed at the stabilization and the continuous improvement of the production process. This plan consists of both technical measures applying Statistical Process Control (SPC), establishing real-time monitoring for key variables, optimizing operating standards, and decreasing special-cause variation and managerial improvements such as quality governance, cross-department communication, accountability for deviations, and a culture of proactive, data-driven decision-making. The combination of these recommendations is meant to provide a production process that is not only very stable and with high capability but also capable of consistently producing the first-class products that the premium Binh Duong market demands and of maintaining HAPPY COW's long-term competitiveness in the Middle-earth region.

III. Analysis of current quality situation

1. Overview and Descriptive Data Analysis of Milk Quality Data

1.1. Input variables overview

The dataset contains 1,059 records, and all observations are complete with no missing values across all eight variables (pH, Temperature, Taste, Odor, Fat, Turbidity, Colour, and Grade). This indicates that the dataset provided by the instructor is fully non-null and ready for analysis without requiring any imputation or data cleaning for missing data.

Figure 1: Descriptive Data Analysis of input variables

The figure provides an overview of the distribution characteristics of all variables in the milk quality data set.

General comments: It is observed that the pH and Temperature variables have a wide range of fluctuations, and many outliers appear, indicating large fluctuations in the process of controlling these parameters. In contrast, the group of sensory variables including Taste, Smell, Fat Content, and Turbidity, had a skewed distribution, reflecting the tendency to focus on certain values. In particular, the appearance of double distribution peaks in pH and Temperature indicates the instability of the manufacturing process between batches, demonstrating the need for improved process control to ensure consistent quality.

1.2 Statistical Analysis (Descriptive Statistics)

	pH	Temprature	Taste	Odor	Fat	Turbidity	Colour
count	1059.00	1059.000	1059.000	1059.000	1059.000	1059.000	1059.000
mean	6.63	44.227	0.547	0.432	0.671	0.491	251.840
std	1.40	10.098	0.498	0.496	0.470	0.500	4.307
min	3.00	34.000	0.000	0.000	0.000	0.000	240.000
25%	6.50	38.000	0.000	0.000	0.000	0.000	250.000
50%	6.70	41.000	1.000	0.000	1.000	0.000	255.000
75%	6.80	45.000	1.000	1.000	1.000	1.000	255.000
max	9.50	90.000	1.000	1.000	1.000	1.000	255.000

Figure 2: Descriptive Data Analysis of Milk Quality Data

Descriptive statistics of seven quality variables, including pH, Temperature, Taste, Odor, Fat Content, Turbidity, and Color, reveal many important characteristics related to the stability of the production process as well as the sensory quality of milk. The median, range, and IQR values reflect the degree of variability of each variable, thereby supporting the assessment of key issues in quality control.

a. Variables related to process control have a high degree of variability.

The two core variables of the production process, Temperature and Turbidity, have a very large degree of variation.

The temperature has an average value of about 44.23°C but ranges from 34°C to 90°C indicates that the heating or cooling process is not stable.

Turbidity, even in binary form, also shows an imbalance when the number of samples in clear and turbid states is almost equal, with a mean = 0.491, meaning 49.1% of samples have turbidity = 1, that is, 50.9% of samples have turbidity = 0. Therefore, the two groups 0 (clear) and 1 (turbid) have nearly equal proportions. This shows that this variable is not strongly tilted towards either side, and the distribution is almost bifurcated. Reflects the possibility of problems in the filtration system or the risk of microbiological contamination in some batches.

b. Sensory attributes show uneven levels of stability.

Sensory variables groups, including Taste, Odor and Fat Content, have important influences on product acceptability.

The majority of the samples met the "good fat content" standard, as evidenced by the relatively high mean fat value of 0.671. As evidenced by the relatively high mean fat value of 0.671.

Odor indicates that the quality is not satisfactory when the majority of the samples were rated as bad odor showing that the mean value = 0.432, which corresponds to 43.2% good odor and 56.8% bad odor. Possible causes could be due to contamination, contamination, improper handling or storage of the input materials.

Flavor showed moderate stability, with more than half of the samples rated as having good flavor (54.7%). This fluctuation may be due to changes in fat quality or microbial changes during storage.

c. Overall quality is governed by four important variables

Considering the distribution behaviors along with the dependency relationships with the determinant variable Grade, it is possible to select four variables which are most important for classification, which are Temperature, Fat Content, Odor, and Turbidity.

Temperature is the most critical element, and even the smallest deviations may lead to quality reduction along with changes in the sensory attributes.

Fat content is strongly correlated with and impacts the overall rating as well as the taste and smell.

Odor is a significant attribute as it is an important determinant of contamination and/or spoilage.

Turbidity is also about quality evaluation because it is usually related to microbiological issues or the issues in the filtering of something, which are the strong problems in the quality of something.

The other three variables such as pH, Color and Taste have weaker impacts.

As for pH, it does have a wide range with a minimum and maximum of 3.0 and 9.5, but the majority of the samples are clearly concentrated in the smaller niche of 6.5 and 6.8. The appearance of extreme values in either direction is more likely the result of measurement inaccuracies, or inferences of strange, atypical patterns as opposed to portraying legitimate integrated shifts in the process of manufacturing. Color is one of the sensory variables and it does show nearly total stasis.

The values for Color ranged only between 240 and 255, indicating that the color for all samples of the milk did not differ and thus, did not present any substantial variation or fluctuations. Hence, Color does not have the variability of the process concerning manufacturing, and no significant sensory issue has arisen requiring any further exploration.

Even though it is taste that the consumer experiences, it is almost certainly overshadowed by the more significant technical and hygienic aspects such as fat content, smell, or turbidity.

1.3. Distribution of the target variable (Grade)

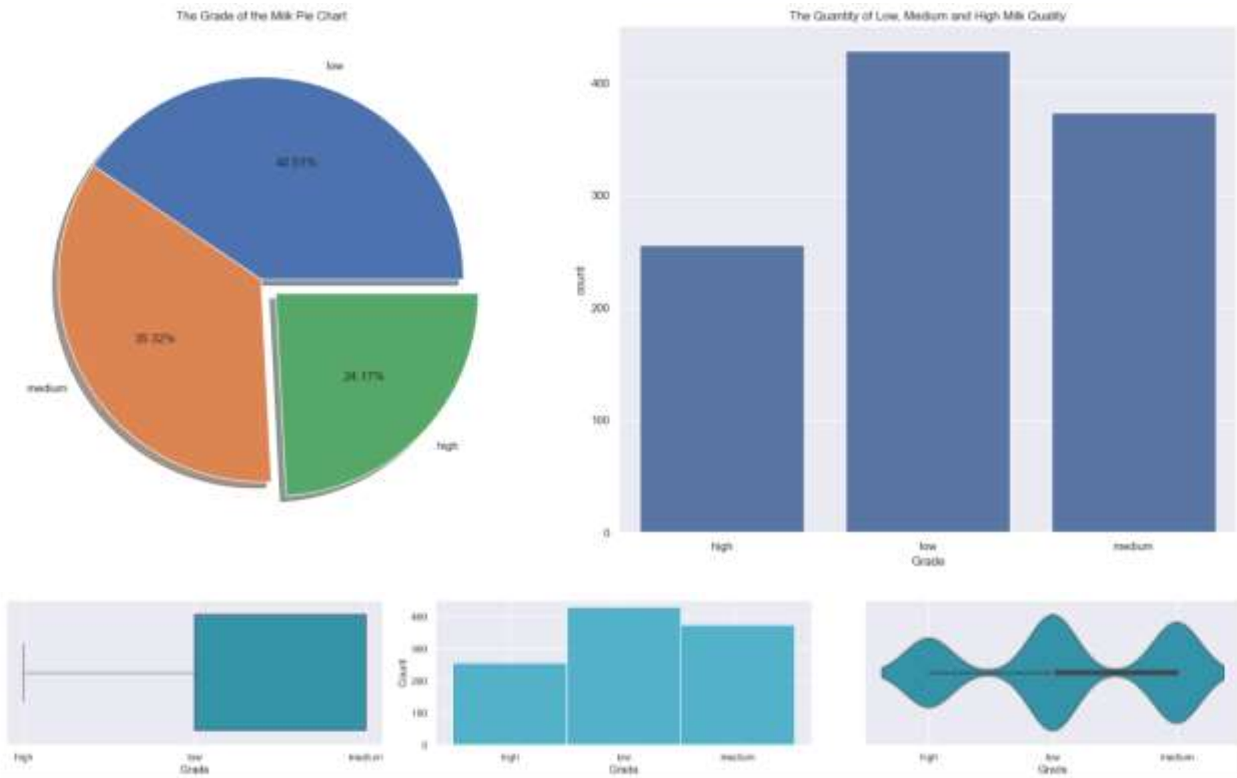


Figure 3: Descriptive Data Analysis of target variable

There is an unequal distribution of sample quality within the three groups in the dataset.

Of the sampled groups, the highest number of samples were of the low-quality milk, at 439, representing 40.5% of the total sample. Average quality also constituted a large grouping, at 360 samples. Lastly, the group with the highest quality but the smallest grouping, with only 227 samples, only 24.2% of the total that were high quality. This shows that the tendency in samples is to show production that primarily concerns the low-quality group, and that the majority of the samples are low-quality tiered.

This is also seen in the bar and histograms, where the apparent trend is decreasing in the number of samples per high and low group. The box and violin plots show the variances of the groups. For the two lower quality groups (the low and average quality milk), the variability is much greater, which suggests that there are some processes that are biased and are introducing instability. On the other hand, the high-quality groups show more well-behaved and tightly varied distributions. Although the number of samples in this group is smaller, the results show that the production process is fully capable of producing good-quality batches when strictly controlled.

Overall, the data visualizations indicate a need for greater process control at particular intervals, for example, temperature control, impurity filtration, and stock feed manipulation. Targeting these measures, data visualization indicates a high and medium quality target production data visualizations indicate a low production quality range.

1.4. Characteristics of the Three Milk Quality Groups (Low – Medium – High)

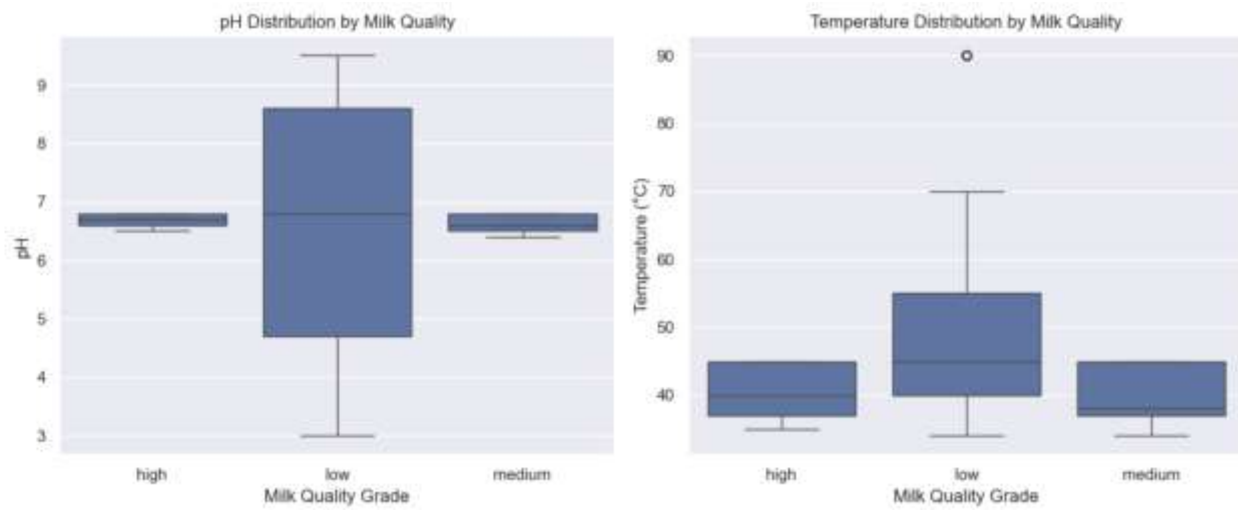


Figure 4: Descriptive Data Analysis of three milk quality groups

a) pH characteristics

The pH value shows a very clear difference between the three quality groups. The high quality group has a tightly concentrated pH in the range of 6.65 - 6.75, with almost no abnormal values. This reflects a stable chemical environment and is less affected by interfering factors such as microorganisms or biochemical changes. The average quality group has roughly similar pH levels, ranging from 6.5 – 6.8, but the wider dispersion shows that the process is not yet completely stable.

On the contrary, the low quality group has extremely large fluctuations, ranging from pH ≈ 3 to pH ≈ 9.5, far beyond the suitable range for fresh milk. This is a clear sign of weak control at many stages such as storage, microbiological exposure or deviations in chemical treatment. This sharp fluctuation not only reduces quality but also indicates the instability of input materials or production equipment.

b) Temperature characteristics

The temperature of the high quality group is maintained quite stable in the range of 37 - 45°C, suitable for standard heating and sterilization processes. The medium quality group also fluctuated in a similar range, mainly from 36 – 46°C, but the greater dispersion showed that the batch-to-batch uniformity was not as high as the high quality group.

The low quality group shows the strongest temperature variation. The values range from 33°C to 70°C, and there are special outliers exceeding 90°C. The presence of abnormally high temperatures can lead to protein denaturation, mineral imbalance and destruction of the microstructure of milk. This shows that it is likely that the heating process is incorrect, the equipment is unstable, or the operating personnel have not complied with technical standards.

c) Comment

In general, both pH and temperature are indicators that directly reflect the level of process control. The high quality group had clear stability in both parameters. The average group has slight fluctuations but is still within an acceptable range. The low quality group in particular shows great inconsistency, showing that the production process needs to be significantly improved to limit deviations and increase the proportion of high quality products.

1.5. Correlation Analysis: Relationship between variables (pH, Temperature, etc.) and Quality Grade

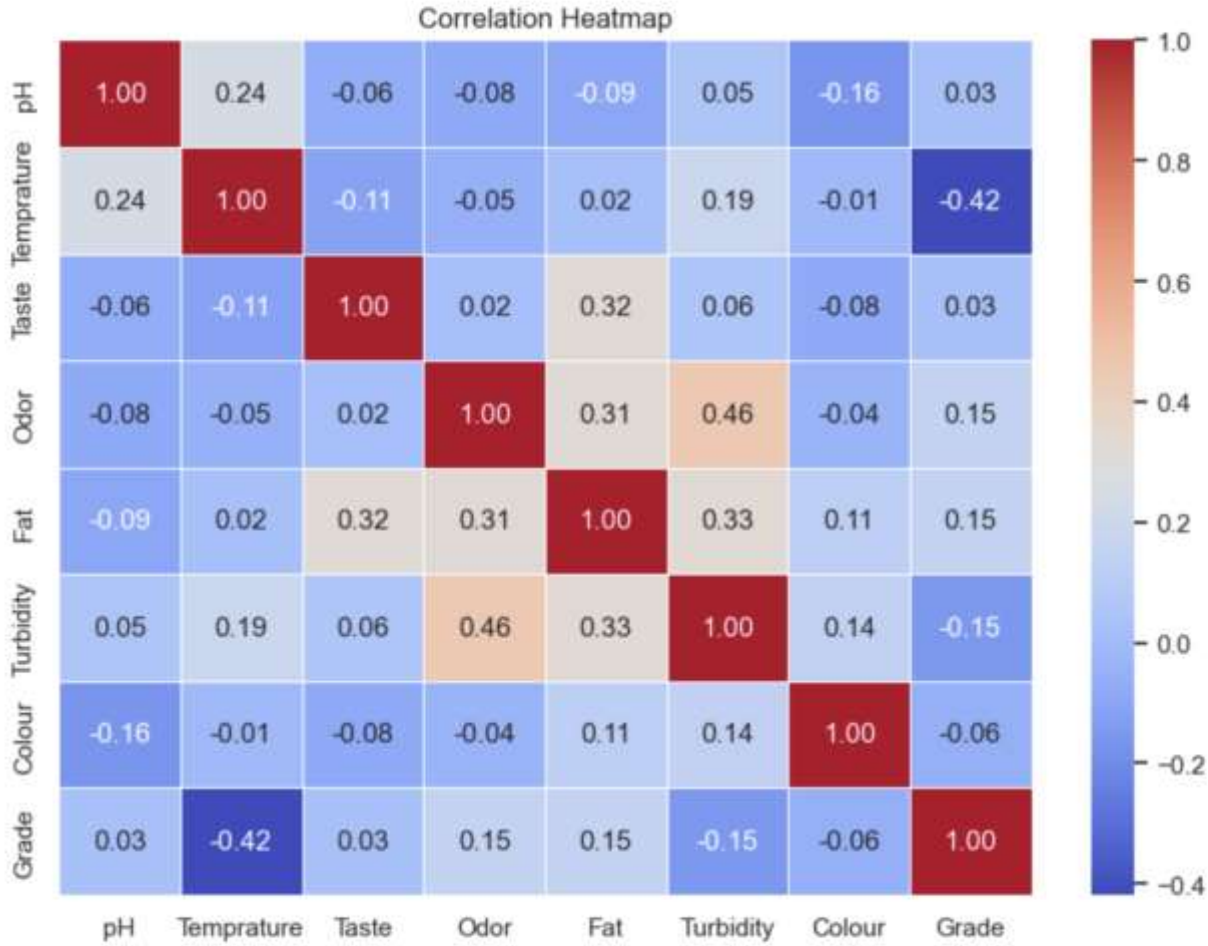


Figure 5: Correlation heatmap which analyzes relationship between variables and quality grade

There are several reasonably powerful positive correlations in the data.

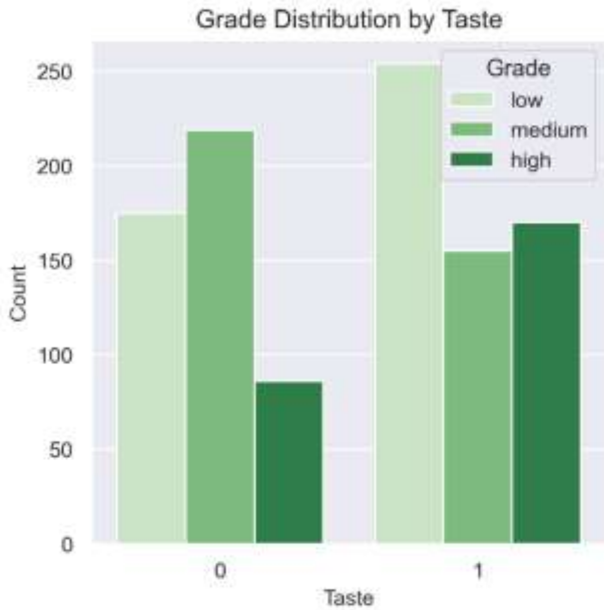
The strongest association was between odor and turbidity (r=0.46), in which milk samples with high turbidity were more likely to have odor complaints. This probably indicates concerns about filtration, contamination, or deterioration of the microbiological quality. In addition, fat content has a (r=0.32) moderate correlation with taste, which is also associated with odor (r=0.31) and turbidity (r=0.33) as well. These correlations indicate that as fat content in milk varies, the milk and its sensory quality undergo a simultaneous state change.

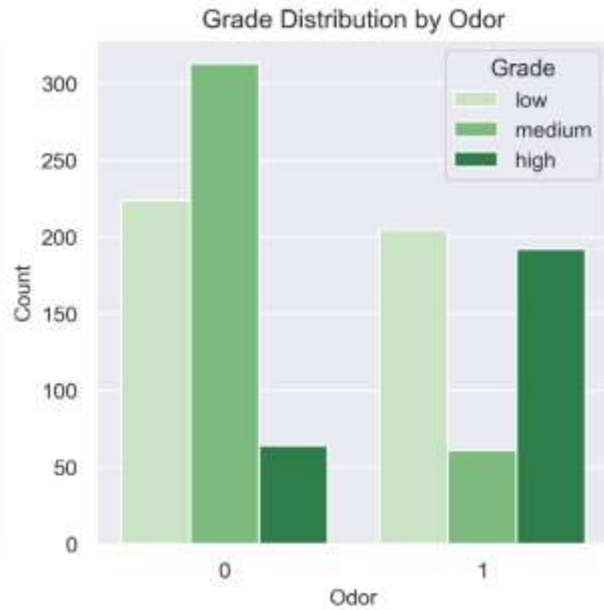
In contrast, variables pH, color, and taste had correlations with quality level that were very low ($|r| < 0.1$), which indicates that these factors were either tightly controlled at a stable range or that these factors were not significant in determining the final quality classification.

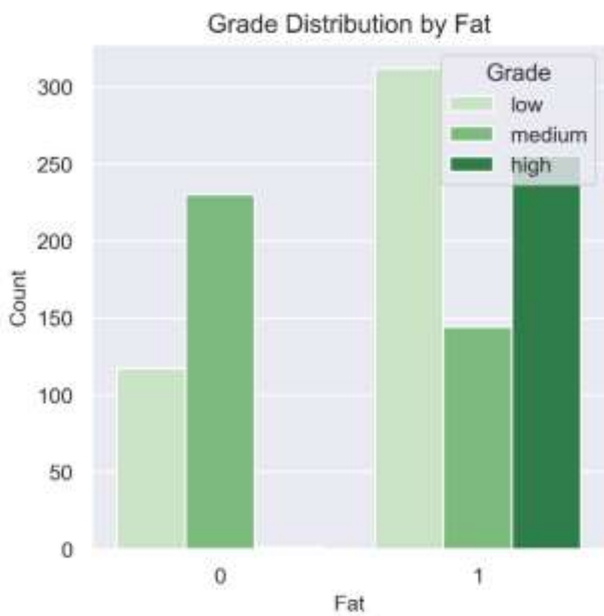
In total, the correlation model indicates that the product of milk, its quality, is heavily determined by the interplay of factors in the production process, in particular temperature, odor, turbidity, and fat content. Conversely, pH, color, and taste are uniformly distributed, and these factors have a minimal role in the classification of the quality groups.

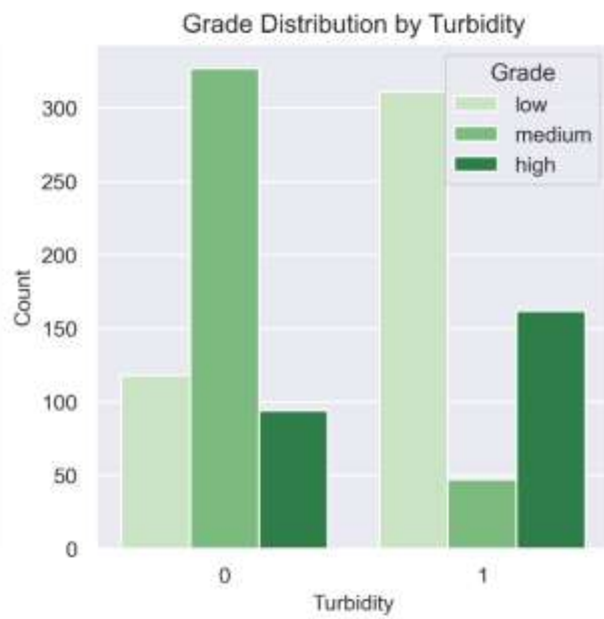
2. Process Performance Evaluation

2.1. Binary variables


Grade Distribution by Taste
Grade
low
medium
high
Count
0
50
100
150
200
250
0
1
Taste


Grade Distribution by Odor
Grade
low
medium
high
Count
0
50
100
150
200
250
300
0
1
Odor


Grade Distribution by Fat
Grade
low
medium
high
Count
0
50
100
150
200
250
300
0
1
Fat


Grade Distribution by Turbidity
Grade
low
medium
high
Count
0
50
100
150
200
250
300
0
1
Turbidity

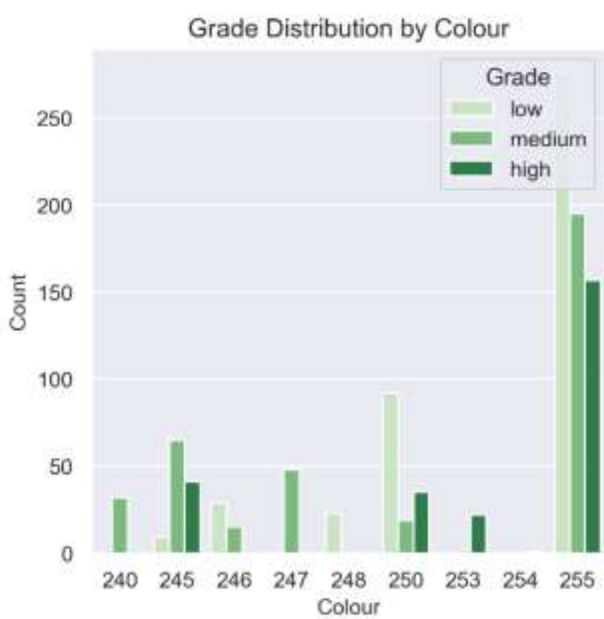

Grade Distribution by Colour
Grade
low
medium
high
Count
0
50
100
150
200
250
240
245
246
247
248
250
253
254
255
Colour

Figure 6: Grade Distribution by Taste, Odor, Fat, Turbidity and Colour

Determining characteristics such as Taste, Odor, Fat, and Turbidity through the Grade Distribution diagrams indicates that there is a noticeable polarization effect of the production method. In several of the attributes being discussed, the amount of grades assigned as High (very good) and Low (very poor) is still greater than the Medium (average) grade. Such a quality control scenario is reflected through the distribution pattern as lack of control in the process and high variation. The situation here is just the opposite; instead of clustering the majority of the products around the average quality level (Medium), which is indicative of a stable process, the output is producing huge volumes of products with very high quality and also a very large number of products with very poor quality at the same time. This means that while one batch might be treated excellently (for example, leading to a High Taste grade), another batch, perhaps due to uneven production or storage, will quickly fall to Low, thus highlighting the necessity to stabilize the entire manufacturing process.

2.2. Continuous Variables Analysis (Temperature, pH, Colour)

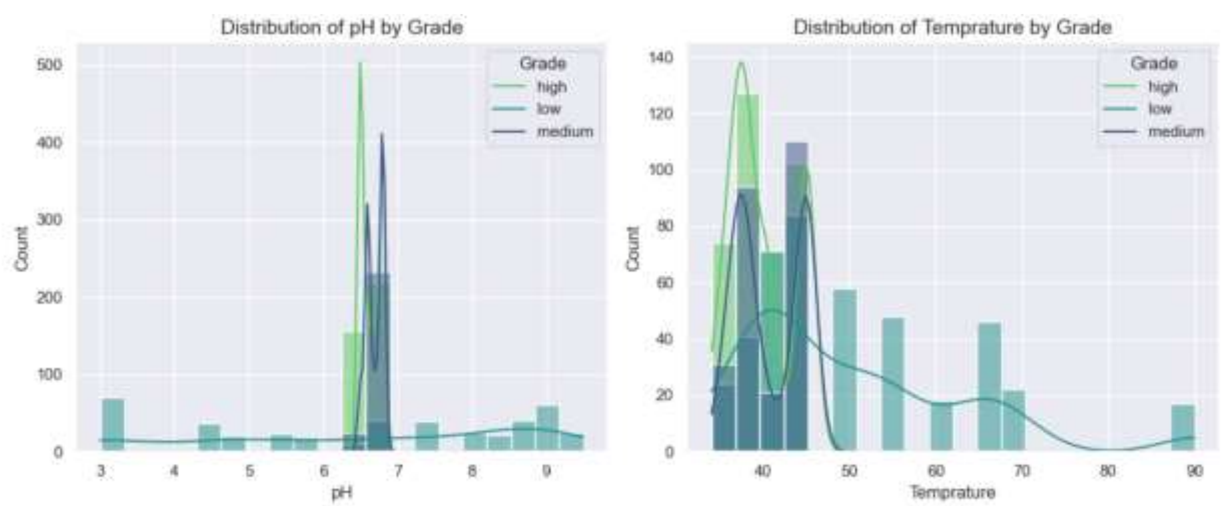


Figure 7: Distribution of pH by Grade and Temperature by Grade

The impact of different factors on milk quality is different according to the analysis of continuous variables. pH has only little impact on the quality of the milk, since the three grades of quality are nearly all between 6.5 and 6.8 which are very close to each other. The pH level of milk is well regulated and is, therefore, not a major distinguishing factor between the different grades of milk quality. Temperature, on the other hand, shows a clear grade differentiation and is considered the most important quality indicator. Quality milk is mainly produced at lower temperatures (typically 38°C - 42°C)while low-quality milk is spread over a large temperature range all the way up to 80°C-90°C. The low-quality group has such a large range because it includes the poorly controlled temperatures that confirm the association between temperature and quality. Finally, continuous Colour shows a similar trend to binary variables, indicating a process-driven split. High- and medium-quality milk is found mainly in the upper colour range (254–255), while low-quality milk is more often in the lower range (240–248). This suggests that defects in milk coloration caused by overheating or oxidation are very evident.

2.3. Assessment: Does the current quality meet the higher standardization requirements for market expansion?

Conclusion: NO.

The present manufacturing system does not completely comply with the higher standardization requirements needed for market expansion based on the total quality grades distribution and variability observed in the main process parameters.

The examination brings to light a Critical Imbalance in the output that is heavily dominated by low-quality milk with approximately 40% of the total output vs. only about 24% by the high-quality milk which is considered frequent failure to meet standards for the premium markets. This situation is worsened and supported by the evidence of Systemic Instability where large swings in the critical variables of temperature, odor, turbidity, and fat content are processing thus creating a polarization effect wherein the batches are either distinctly high-quality or clearly low-quality so that it is hard to scale the reliable medium or high-grade production of milk. The use of extreme processing temperatures, inconsistent fat levels, and high turbidity in the low-grade samples is an indication of a basic inadequacy in control. The process can yield high-quality milk that is stable under optimal conditions (as shown by the close distribution of high-grade characteristics) but cannot consistently maintain the optimal conditions across the whole production range. Hence, the current quality performance is not up to the level of the more demanding market expansion objectives, and at the same time, it is necessary to introduce a substantial improvement in process control, monitoring, and standardization in order to achieve the reliable supply of milk for higher-tier markets.

IV. Identify the current situation and specification

1. The Hypothesis Testing on Variable Independence

1.1. Introduction

The hypothesis testing phase aims to explain the statistical relationship between the variables related to the quality of the milk that can be perceived through the senses, the physical characteristics, and the process aspects. With the respective dataset including both categorical and numeric variables, a range of statistical test procedures, specifically the Chi-Square, ANOVA, and Pearson tests, was conducted.

1.2. Rationale for Using Multiple Tests

The application of Chi-Square tests, ANOVA, and Pearson correlation analysis is methodologically justified by the differing data types and analytical objectives:

Chi-Square tests assess dependency among **categorical** sensory and physical variables.

ANOVA evaluates whether **continuous variables** differ significantly across Grade levels.

Pearson correlation identifies linear associations among **continuous variables**.

Using these complementary methods ensures construct validity and provides a holistic understanding of how process variables interact to shape milk quality outcomes.

	Variable 1	Variable 2	p-value	Conclusion	Test \
0	Taste	Turbidity	7.966269e-02	Independent	Chi-Square
1	Odor	Taste	6.101446e-01	Independent	Chi-Square
2	Odor	Turbidity	8.049347e-50	NOT independent	Chi-Square
3	Fat	Taste	1.035843e-25	NOT independent	Chi-Square
4	Fat	Odor	2.736139e-24	NOT independent	Chi-Square
5	Fat	Turbidity	1.752000e-26	NOT independent	Chi-Square
6	Fat	Grade	8.519530e-59	NOT independent	Chi-Square
7	Grade	Taste	2.532332e-10	NOT independent	Chi-Square
8	Grade	Odor	2.363640e-48	NOT independent	Chi-Square
9	Grade	Turbidity	5.699600e-69	NOT independent	Chi-Square
10	NaN	NaN	6.405242e-01	Independent	ANOVA
11	NaN	NaN	9.787957e-66	NOT independent	ANOVA
12	NaN	NaN	1.327858e-16	NOT independent	ANOVA
13	pH	Temprature	6.679096e-16	NOT independent	Pearson
14	pH	Colour	7.214234e-08	NOT independent	Pearson
15	Temprature	Colour	7.820435e-01	Independent	Pearson

Figure 8: The summaries of tests

1.3. Results of Hypothesis Testing

The hypothesis testing results reveal clear dependency patterns among the variables that influence milk quality.

1.3.1. Chi-Square Tests for Categorical Variables

The data reveals the emergence of statistical dependence among the variables in each set sensory and physicovariables, signifying a strong link between the quality variables. In particular, Odor depends on Turbidity ($p \approx 8.01e\text{-}50$); Fat on Taste ($p \approx 1.03e\text{-}25$); and Fat on Odor ($p \approx 2.73e\text{-}24$) and on Turbidity ($p \approx 1.75e\text{-}26$). Moreover, the Grade has statistical dependence on the variables Taste, Odor, Fat, and Turbidity in all cases, and these results imply that defects in the senses and in the physical characteristics usually occur together, and that when the deterioration in one characteristic takes place, it usually takes place in the others too. Thus, when Fat content in the sample is low, the Odor and the Taste may be defective together.

One exception appears in the connection between Taste and Turbidity, where the test reveals statistical independence ($p \approx 0.079$). This confirms the lack of direct relation between an unfavorable taste and sample cloudiness. The link between Grade and several variables, namely

Taste, Odor, Fat, and Turbidity, adds evidence supporting the importance of variables in the definition of product quality.

1.3.2. ANOVA for Continuous Variables Across Grade Levels

For **continuous variables**, the **ANOVA** tests show that both Temperature and Colour vary significantly across Grade levels, indicating that these process-related factors also contribute to quality differentiation.

The ANOVA results reveal that **Temperature** and **Colour** differ significantly across milk quality grades ($p \ll 0.05$), indicating that these process-related variables contribute meaningfully to grade differentiation. Conversely, **pH** does not show significant variation among grade levels ($p \approx 0.641$), suggesting it is not a direct driver of Grade classification in this dataset.

1.3.3. Pearson Correlation Analysis

Pearson correlation coefficients demonstrate strong linear relationships between:

pH and Temperature ($p \approx 6.68 \times 10^{-16}$), and

pH and Colour ($p \approx 7.21 \times 10^{-8}$).

The Pearson correlation tests provide additional context: pH and Colour exhibit a statistically significant but pH and Colour exhibit a **statistically significant linear relationship** ($p \approx 7.21e-08$), indicating a clear association between acidity and colour, while Temperature and Colour are statistically independent ($p \approx 0.782$). This suggests that these continuous variables influence quality through separate mechanisms rather than through the same underlying source of variation.

Overall, the hypothesis testing results demonstrate that milk quality is not driven by any single factor but rather by a combination of strongly connected sensory attributes (Odor, Fat, Taste, Turbidity) and key process variables (Temperature, Colour). These patterns confirm that improving quality performance will require coordinated improvements across multiple points of the production system rather than isolated adjustments to individual variables.

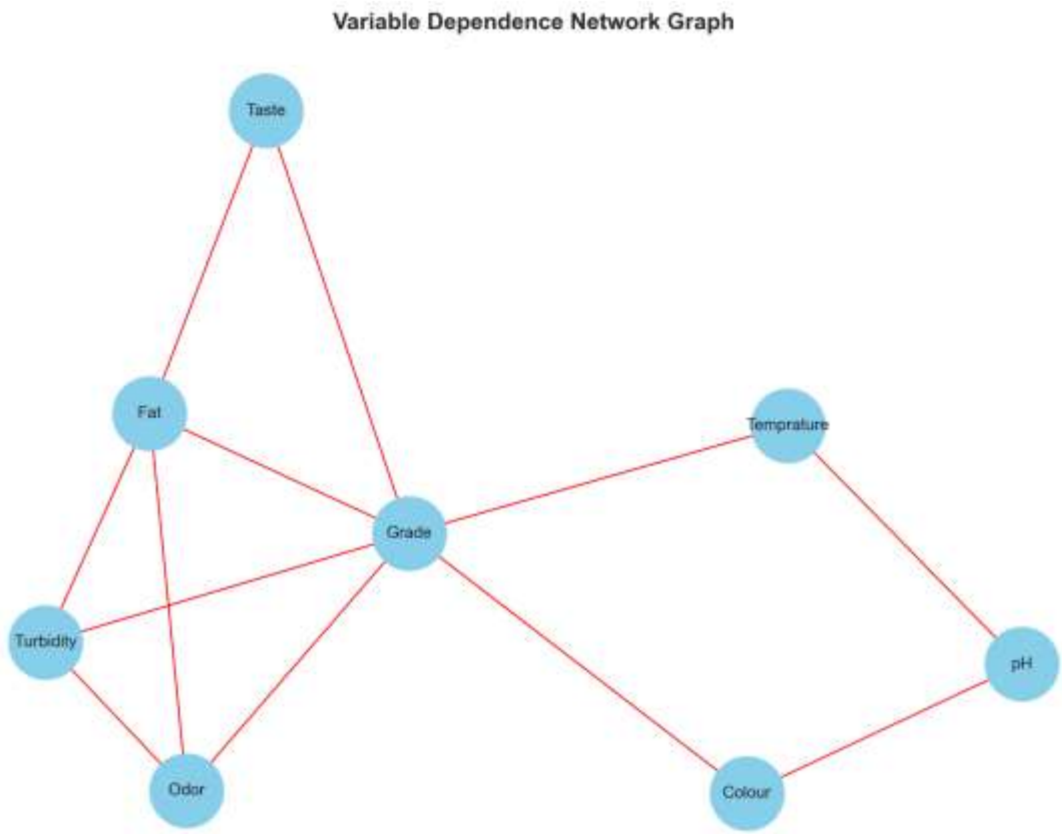


Figure 9: Variable dependence network graph

1.4. Identification of Critical-to-Quality (CTQ) Variables

Based on the combined outcome from the Chi-square analyses, ANOVA, and Pearson Correlation analyses, some variables have emerged as Critical-to-Quality variables, denoted CTQs, where they provide the strongest contribution in defining the quality classification process. The basic CTQ variables are Odor, Fat, Turbidity, and Temperature, where all variables have displayed remarkably high statistical correlations with the resulting Grade. Moreover, their lower significant values reflect the manner in which the changes in the variables closely associated with the product quality, thereby introducing the need for an unprecedentedly high quality management process. The remaining variables, namely Taste and Colour, are considered secondary variables under the CTQ, where they moderately associate with the resulting grades, despite the less prominent contribution, they still play an important role in defining the different levels of product quality. The remaining variable, pH, was determined as the non-CTQ. Despite the statistical correlations between pH, Temperature, and Colour, the pH conditions fail in defining distinct grades, and hence, the pH effect on product quality indirectly arises.

1.5. Failure Pathways

Two primary failure pathways are identified:

a) Process Variation Path

pH → Temperature → Colour → Grade

The changes that occur in Temperature trigger changes in pH and Colour, and subsequently, the degradation in Grade. The relationship among the variables reveals the defects resulting from the malfunctioning of the equipment, uncontrolled temperatures, and unmanaged operations.

b) Sensory Defect Path

Odor → Turbidity → Fat → Taste → Grade

Poor Odor triggers a chain reaction perceived in terms of defects in sensation, namely in Increased Turbidity, Unstable Fat, and Impaired Taste, culminating in Lower Grade. The chain reaction reveals possible issues arising from the quality, purity, and/or efficacy of the filtration process.

Hypothesis testing and analyzing interdependencies among variables reveal the major failure modes and the corresponding paths through which the process of deterioration in the quality of the product takes place. The first path, namely the Process Variation Path, takes the path pH → Temperature → Colour → Grade. Here, the oscillations in the value of Temperature cause changes in the value of pH, and in turn, this affects the value of Colour, resulting in the eventual lowering of Grade. The reason could be the malfunctioning process due to uncontrolled temperatures.

The other path, called the Sensory Defect Pathway, traces the sequence Odor → Turbidity → Fat → Taste → Grade. In this process, the deterioration in Odor sets in a chain reaction in the form of other defects in the senses, namely, rise in Turbidity, fluctuation in Fat, and decrease in Taste, all leading to lower Grades. These defects reveal the deficiencies in the quality and processing conditions of the raw materials.

Together, these process pathways reveal the complex aspects of quality failure and the need for process stabilization, in addition to better management of the quality characteristics.

1.6. Summary of Findings

Generally, the hypothesis testing establishes that the quality of milk does not depend on a single factor, rather on the complex relationships among the affected variables. The strong statistical links existing among the variables Odor, Fat, Turbidity, and Temperature, and the evidence supporting the relationships among the other variables like pH, Temperature, and Colour, confirm that the quality results from the complex performance of the system variables. Therefore, improvements in the quality of the product cannot be realized through single variables, rather through an integrated approach at the system level, where the quality would be assured through proper monitoring and attention at the system level, particularly focusing on Critical-to-Quality variables.

2. Process variation on Temperature and pH

2.1. Evaluation of Current Process Stability

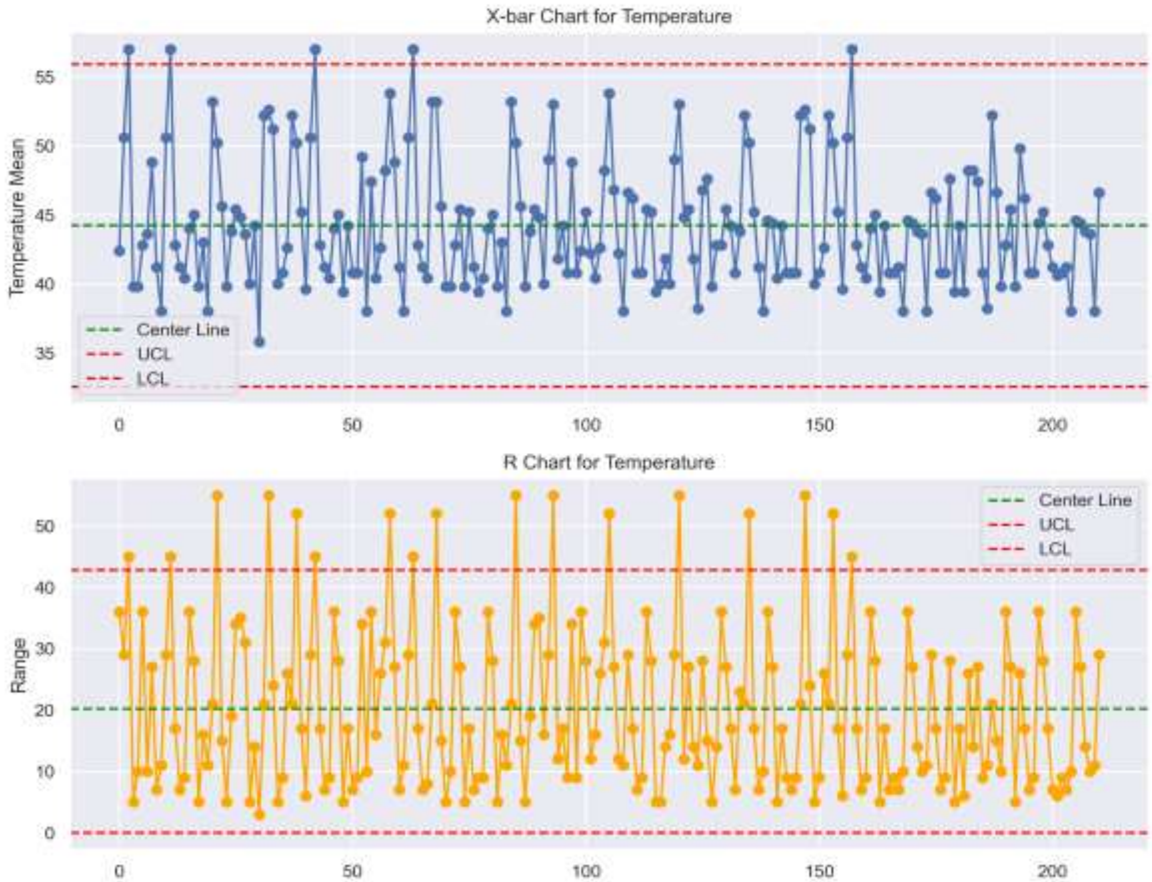


Figure 10: X-bar and R-Charts for Temperature in current process

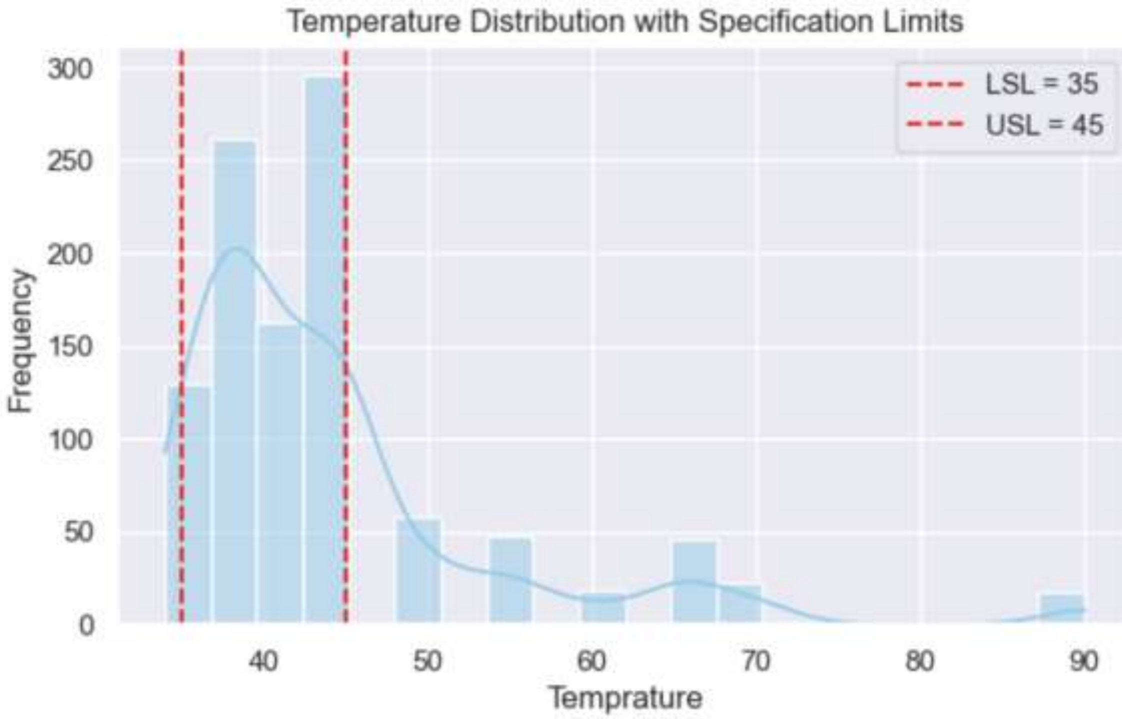


Figure 11: Temperature distribution with specification limits in current process

X-bar and R-Charts for Temperature:

The X-bar and R charts for temperature reveal beyond doubt that the process concerning the production of milk in the company is not under control.

In the X-bar chart, the range of variations in the subgroups varies from 36°C to 57°C, and this in most cases tends to touch and even exceed the Upper Control Limit. There is, therefore, a large amount of fluctuation in the process mean, and this tends to reveal the absence of process control in the pasteurization process. In a stable process, the subgroups would ideally remain near the Center Line and be confined to the control limits. In the present scenario, neither condition has been achieved.

The R chart provides further evidence in this regard, and the range in temperature in the subgroups tends to touch the upper control limit. This tends to reveal the absence of process control in the process. Furthermore, the large variability in the range tends to reflect the process characteristics, and the lack of ability to regulate the high variability tends to reveal, beyond doubt, the absence of process control.

Together, the X-bar and R charts show that temperature conditions are not in a state of statistical control. The process has both inter-group and in-group variations, X-bar and R, respectively, and hence, the process has a systematic, rather than an irregular, cause. In the absence of temperature control, the factory would likely provide inconsistent quality performance, including the constant drifting away from the optimal temperature range of 38 – 42°C, necessary and sufficient for high quality in the milk.

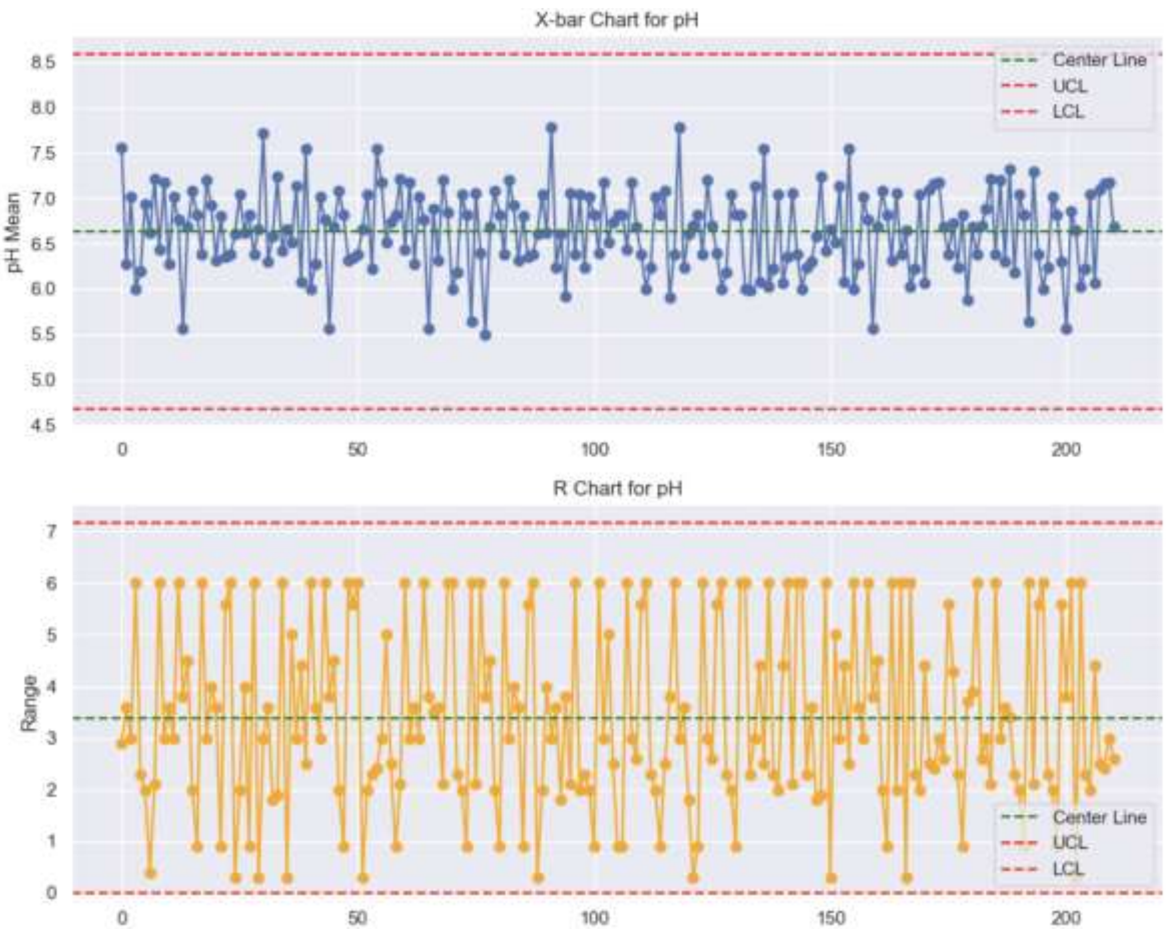


Figure 12: X-chart and R-chart for pH in current process

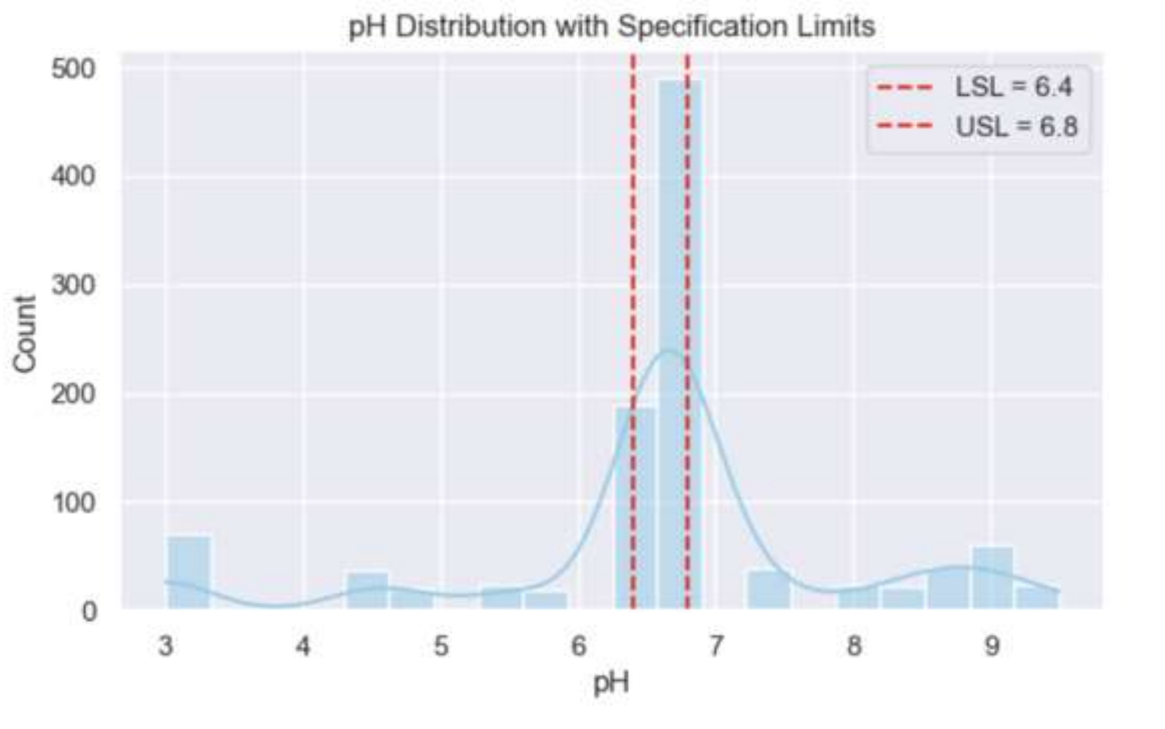


Figure 13: pH distribution with specification limits in current process

2.2. Specification Setting for High-Grade Milk

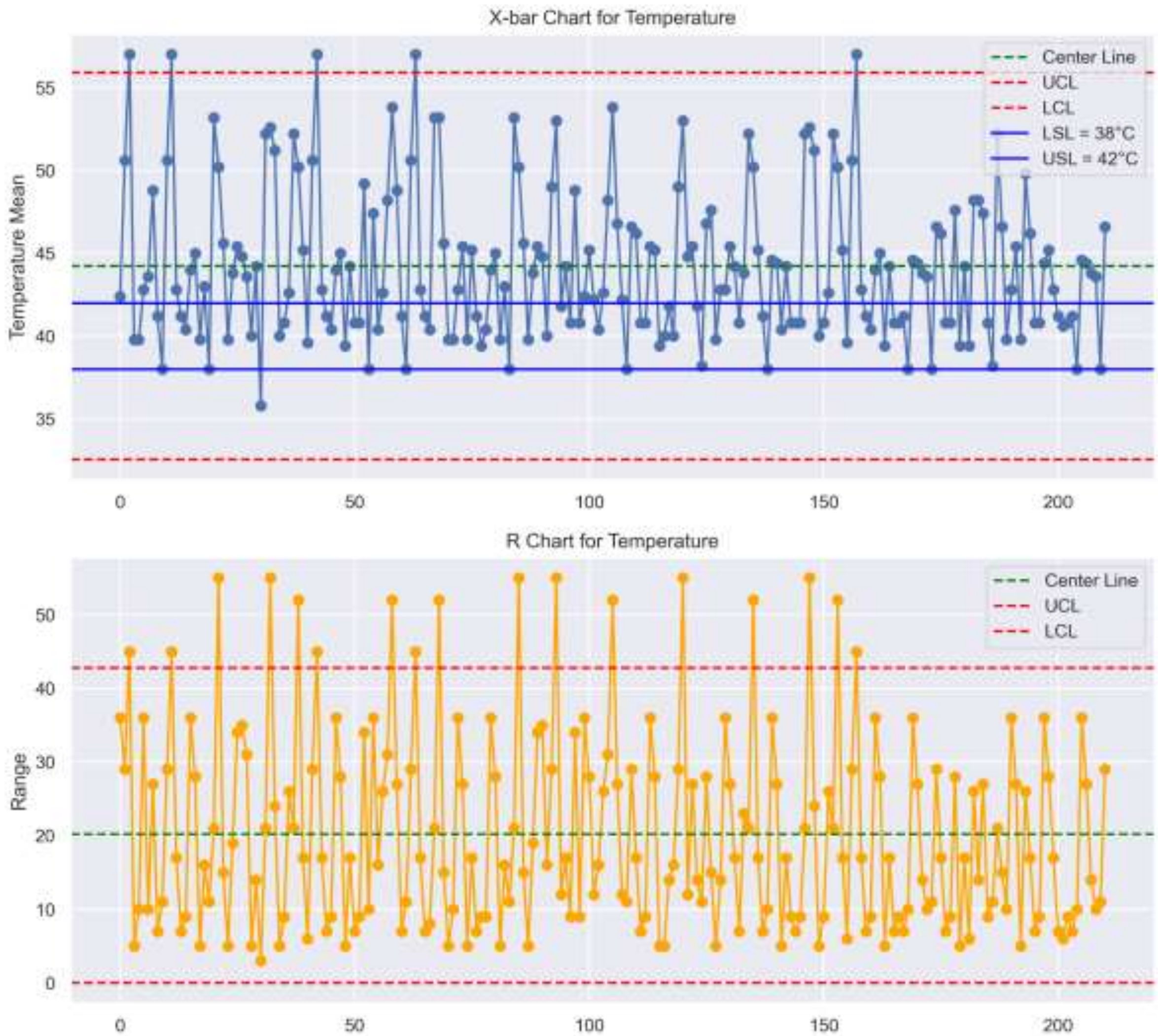


Figure 14: X-chart and R-chart for temperature in improvement process

Although the High-grade temperature distribution ranges from 35°C to 45°C, its probability density is not uniform. The highest-density region (natural process cluster) is concentrated between approximately 38°C and 42°C, while values near 35-37°C and 43-45°C represent low-density tails caused by process noise or measurement variation. Therefore, the specification limits (LSL - USL) were set based on the stable region of the High-grade cluster (38-42°C), rather than the full observed range, which includes unstable process behavior.

The combined X-bar and R chart with specification limits (USL = 38°C and LSL = 42°C) enables better assessment of the process stability and capability in respect of high quality and stable temperature conditions. The X-bar chart reveals that the average temperatures in the subgroups range from 38°C to 56°C, and most of the data points fall beyond the range of 38-42°C. This observation reveals the high variability in the process, and there appears to be a constant failure in producing milk in the corresponding temperature range required for high quality. The use of temperatures beyond the upper specification limit appears frequent, resulting in the deterioration of quality, reducing the nutritional value, and affecting other characteristics.

In addition to the violations of the services specifications, the process appears highly statistically unstable. The subgroup means are drifting in and out of the statistical control limits, indicating lack of control. While the performance means in a stable process would fluctuate in a predictable manner about the center line, the performance here appears irregular and strongly suggests the presence of special-cause variation, usually due to the inconsistency in the heating systems, the operators, and the malfunctioning equipment.

The R chart confirms the evaluation because large and irregular variations in the temperature range are observed. Quite a number of the subgroups are nearing the upper range control limit, and this reveals high temperatures even in the smaller samples. This type of process exhibits uncontrolled changes, and it means the causative factors affecting the process are responsible for both short- and long-term variability.

In general, the combination charts prove that:

The temperature process lacks statistical control because the SPC limits are not met. Furthermore, the process does not meet the specification limits for high-quality milk, ranging from 38-42°C. The variability in the between-group and within-range means tends to be too high, ensuring that the randomness encountered in the earlier scenario isn't systematic. Without the measures needed, like the re-calibration of the heating systems and better management and operation controls, it is less likely that the temperatures needed in producing high-grade milk would always be achieved. In particular, the importance of temperatures and other CTQ variables in the process, and the need to first stabilize the process, and later on pursue, more standardization, particularly in high quality.

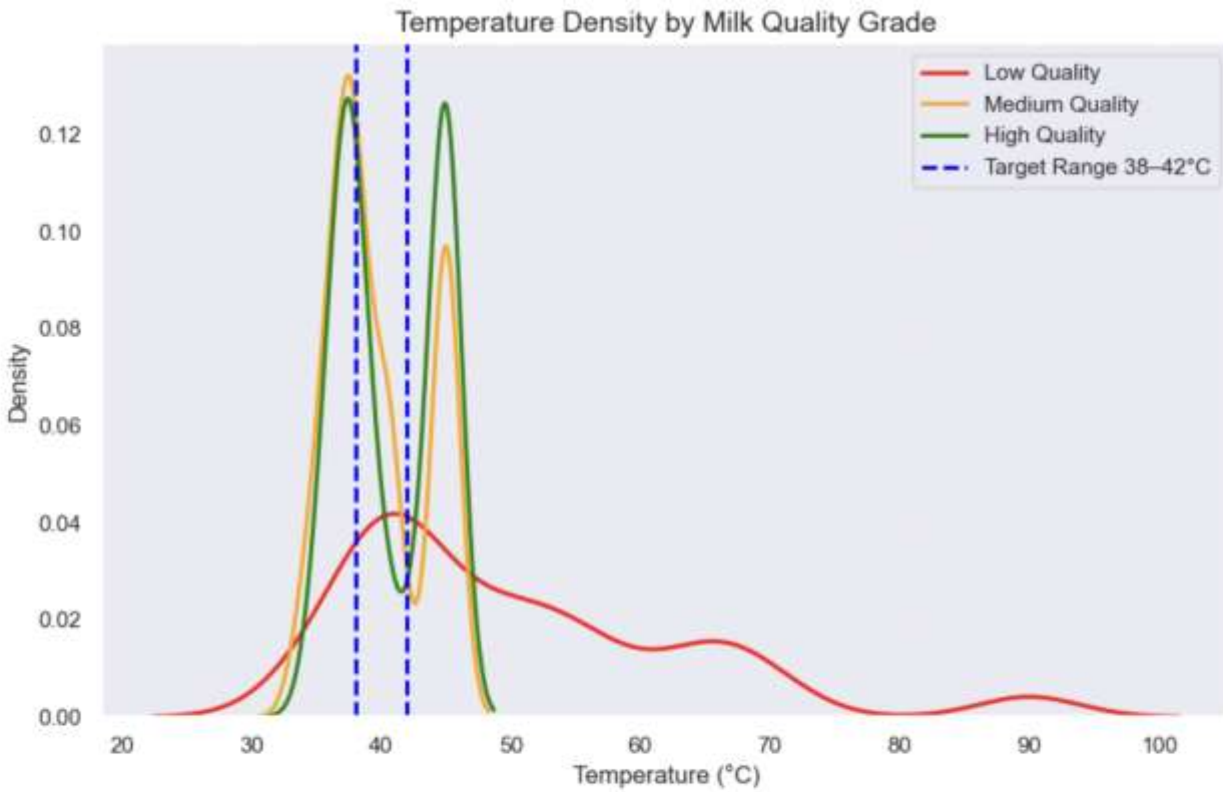


Figure 15: Temperature Density by milk quality grade

2.3. Rationale for Setting the Target Temperature at 38 - 42°C Instead of the Medium-Quality Range

That the target for the process should be set between 38-42 degrees Celsius instead of the range for medium quality is supported by statistical evidence. This range includes the high quality range.

2.3.1. Medium-Quality Milk Does Not Represent a Stable Process Zone

A medium quality range cannot serve as a reference point for process targeting since there is no visible grouping around the temperature. This range covers a wide range of values (34-45°C) without a central point. Essentially, medium quality refers to a process point of instability in the context of being low or high quality. There seems to be no controlled process point of medium quality. This makes medium quality neither a targetable point for processes nor a viable point to support specifications.

2.3.2. High-Quality Milk Exhibits a Clear, Natural, and Stable Temperature Cluster

Contrasting to the above, the high-quality group represents a clearly delineated and statistically robust clustering point range between 38-42oC. In this range, the variability of the values is low, but there is a sharp peak. This range also represents a natural processing point in which the heating processing always operates correctly. Indeed, a temperature range of 38-42oC well represents the "voice of the process," in the sense that it ought to be the reference point for defining control limits.

2.3.3. Process Targets Must Align With the Voice of the Customer and Business Requirements

The goal selected also needs to relate to the strategic vision of the business. The business aims to produce high-quality milk to meet customer needs and to position itself more effectively in foreign markets. To establish a target in the medium quality range simply because achieving the target would be less difficult would go against the strategic aims of the business. There would be no advantage in the quality achieved to position the business effectively in the market.

2.3.4. A Medium-Quality Target Would Not Improve Process Stability

The Statistical Process Control analysis of the X-bar/R chart results demonstrates that the current temperature process has a statistical problem in terms of high variability (34-90°C) and very low values of Cp and Cpk. Even if the facility chooses to target the medium quality band of 34-45°C, the process would remain unstable. There would also be no hope of meeting customer or regulatory specifications. Choosing a larger target range would not solve the problem of special causes of variation; instead, a less demanding target would be adopted.

2.3.5. High-Quality Targets Drive True Continuous Improvement (CI)

An authentic continuous improvement process needs to have goals for reducing variation, increasing the capability of the process, and approaching the customer-specified quality range. Only the high-quality range (38-42°C) satisfies all of these conditions. Setting a process goal of the high-quality range would allow the facility to head in the direction of improvement instead of compromise.

3. Process Capability Analysis (Cp and Cpk)

$C_p = (USL - LSL) / (6 \times \sigma)$

$C_{pk} = [Z(min)] / 3$

$Z(USL) = (USL - \bar{X})/\sigma$

$Z(LSL) = (\bar{X} - LSL)/\sigma$

With a mean of 44.23°C, a standard deviation of 10.10°C, capability indices of both Cp = 0.066 and Cpk = -0.073, the statistical evidence suggests that the existing process is unable to support the manufacture of high-quality milk within the specified limits (LSL = 38°C, USL = 42°C).

With a Cp of 0.066, the variation of the overall process definitely exceeds the specified tolerance range since 0.066 < 1. This implies that the variation of the temperatures recorded is very high to the point that even if the process average was exactly at the center point, the range of the points would still be beyond the specifications.

A Cpk value of -0.073 is even more problematic since the negative Cpk index points to the fact that the process center lies beyond the limits of specification. Given that the center of the process was at 44.23 °C, well above the USL of 42 °C, there was no ambiguity about the positive bias of the process.

These indices, when considered together, show that the present temperature control process satisfies the following conditions: The temperature control process cannot be performed (since Cp ≪ 1).Notice that the process lacks centering and violates the temperature specifications every time (Cpk < 0). There is excessive variation. This variation may be a result of uncontrolled process shifts or unstable equipment. A high-grade quality of milk cannot be produced in the above conditions even before the evaluation of the remaining characteristics (Odor, Fat, Turbidity, Taste).

The Cp & Cpk analysis further validates the previous SPC analysis performed on the X-bar/R control chart that the temperature control process in the facility was highly unstable. This calls for urgent measures to be taken to stabilize the process. In the absence of improvements in the process capability, the present process will continue to be unsuitable for the production of quality or export quality products.

4. Evaluation

According to the overall analysis that also incorporates the distribution analysis, hypothesis testing, identification of CTQ (Critical to Quality) factors, and statistical process control, several limitations in the current production process are evident in its current form, both in its stability and operability, thus not being able to assure the process of sustaining a high quality.

First, the allocation of milk grades in accordance with standards indicates that the production of high-grade milk is within a range of 24, with medium and low-grade milk continuing to prevail. Such unbalance represents the core issue of the process: the system is yet to be run steadily under normal conditions and generate high-quality products. High polarization on major variables, including Odor, Fat Content, Turbidity, and, in particular, Temperature, means that the process swings between the acceptable and unacceptable operation conditions rather than having a constant control operating system.

Temperature, as one of the CTQ variables, was the most deficient. The X-bar and R charts showed that the process was not under statistical control, and the values of the group averages, more often than not, were above the statistical control limits, besides the technical requirement range of 38-42. By these violations, the heating system and pasteurization process were not completed with the required consistency and precision. This instability greatly limited production of high-grade milk because temperature creates a direct impact on microbiological safety, enzyme activity, flavour, and fat stability. Moreover, the big short-term variations that were evident in the R chart illustrated the lack of equipment control and the lack of consistent operation, which continued to add to the variability of the whole process.

The hypothesis testing also proved the above: quality is highly dependent on numerous variables that are closely related to one another, including Odor, Fat Content, Turbidity, and Temperature. Such high dependency implies that the unstable situation in one area will result in the destruction of other areas, which develops a compounding quality load.

When combined, the evidence above points to the fact that the existing process is not stable and able to comply with the stiff requirements of entering the premium product segment. High level of variability, high occurrence of technical standards breaches, and poor grade of milk are all indications of a reactive process instead of a proactive and repeatable control. In the absence of the detailed enhancement of the process standardization, equipment calibration, and real-time control, the production line can hardly support the strategy in the expansion into the high-end market segment.

To sum up, the existing process fails to comply with the operational needs of the high-quality market. In order to achieve expansion, companies must pay attention to stabilization of key CTQ variables, in particular temperature, and reduce undesirable fluctuations and implement more stringent control measures. Businesses can be assured of increasing production to high-end customers only when the process is in sustained statistical control and it has high technical standards.

5. Improvement areas

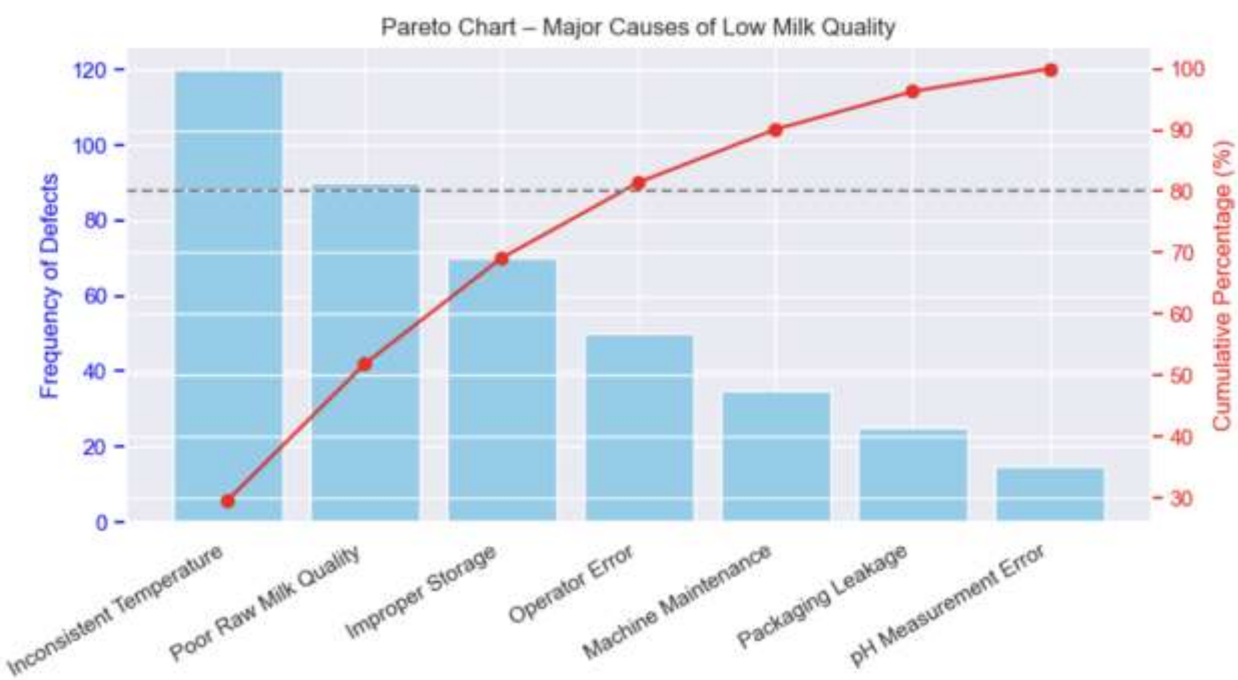


Figure 16: Pareto chart-major causes of low milk quality

The invention of Pareto chart was based on the systematic establishment of the possible root causes that influenced the quality of milk. The six causes listed in the chart were obtained in a two complementary ways. To begin with, an accumulated insight was gained through the analytical phases carried out in the previous stages of the project such as SPC control charts, hypothesis testing, correlation analysis, as also the predictive modeling process. These evaluations continued to point out common problems associated with fluctuations in temperature, variability in raw milk, and decay of sensory attributes. Second, their results were cross-validated with the 6M Framework (Man, Machine, Method, Material, Measurement, Mother Nature), which is a well-known framework in total quality management to classify the sources of variation. The chosen causes can be categorized under each of the 6M categories; hence, they are inclusive and cover all aspects of human and technical.

The Pareto distribution that results indicates that most of the quality failures are due to process instability and raw material failures and not due to single errors or rare incidents. Specifically, three causes, including Inconsistent Temperature Control, Poor Raw Milk Quality and Improper Storage Practices have more than 80% of the total defects. This is the same concentration as the classical 80/20 principle, which proves that few high-impact factors are leading to the most quality deterioration in the production system.

The following findings also support the fact that there are two prevalent failure pathways that influence the end milk grade:

5.1. Process Variation Pathway

Temperature → pH → Colour → Grade

This route shows how changes in the environment and operation are spread out by chemical milk properties. Lack of temperature control leads to imbalanced pH levels, which in turn interfere with colour and eventually reduce the quality grade at the end. This mechanism coincides with the 6M components of the Mother Nature, Machine and Method.

5.2. Sensory Defect Pathway

Odor -turbidity- fat- taste- Grade

This route is an indication of the quality of raw materials and their storage condition on how milk will taste. Weak odor, turbidity, fat, or taste would be highly linked to low quality of incoming raw milk and improper storage, which fall in the Material and Method dimension of the 6M framework.

Considering this evidence, the improvement process should focus on the factors having the highest contribution of defects and most critical systemic impact. In particular, the company is to:

(1) improve temperature control and monitoring,

(2) establish more stringent supplier selection and verification of the quality of raw milk, and

(3) unify storage procedures so as to maintain uniformity between shifts and production batches.

Therefore, it focuses on these high-impact areas, HAPPY COW Ltd. will be able to minimize the variation in the processes, obtain a high percentage of high-quality milk, and enhance the capacity to correspond both to internal standards and to the expectations of the market. This concern aligns with the TQM principles, which focus on going to the roots of problems, process stabilization, and continuous improvement as the directions toward higher levels of operation.

V. BUILDING THE MILK QUALITY PREDICTIVE MODEL

1. Purpose

The Milk Quality Classification Model aims to improve HAPPY COW Ltd.'s capability to meet quality standards through automation and real-time decision-making. By categorizing milk samples into Low, Medium, and High quality, it supports the company's strategic goal of entering high-demand markets. The model also enhances quality management by providing standardized assessments, decreasing human subjectivity, boosting operational efficiency, and preparing the company for market growth.

Traditional quality classification methods rely heavily on manual assessment, which is subjective, unstable, and prone to errors due to sensory fatigue. Applying the prediction model helps classify milk batches based on measurable variables, eliminates subjective errors, and ensures consistency across work shifts.

Distribution analysis shows that only 24.17% of the milk is of high quality, which is much lower than the requirements in markets like Binh Duong. The prediction model helps identify batches that meet standards and separate out defective batches before packaging, ensuring that only acceptable products are distributed.

The company's improvement plan includes: Input Control – Process Control – Output Control. Predictive models play a crucial role in the Output Control stage, complementing optimization activities such as temperature control and sensory improvement.

2. Methodology

2.1. Data Preparation

The data was divided into two distinct groups to facilitate the model-building process. The prediction matrix (X) includes measurement variables such as pH, Temperature, Flavor, Odor, Fat content, Turbidity, and Color, all of which are important factors determining milk quality. The target vector (y) is the Grade variable, which represents three quality levels: Low – Medium – High. This X-y structure separation ensures the model learns correctly from the input variables and accurately predicts the output. At the same time, the variables in X completely match the CTQs (Critical-to-Quality) that were identified thru hypothesis testing and SPC control charts.

2.2. Standardization

Although Decision Trees do not technically require data normalization, the team still applied this step to ensure consistency across the entire machine-learning pipeline and to maintain flexibility for testing additional models in the future. Normalization also helps reduce the imbalance between continuous variables (such as Temperature) and binary variables, preventing any single feature from dominating the learning process. Importantly, the scaler was fitted on the training set and only applied to the test set to avoid *data leakage* and preserve the integrity of the model’s performance evaluation.

2.3. Train–Test Split

To assess the model’s generalization capability, the dataset was divided into 80% training and 20% testing subsets using *train_test_split* with a fixed random seed (random_state = 42) to guarantee reproducibility. This process produced the following partition sizes: X_train: 847 samples, X_test: 212 samples, y_train: 847 labels, and y_test: 212 labels. Such controlled sampling ensures that the evaluation metrics accurately represent the model’s performance on truly unseen data, thereby providing a reliable measure of predictive effectiveness.

3. Model Results and Evaluation

Decision tree Model:

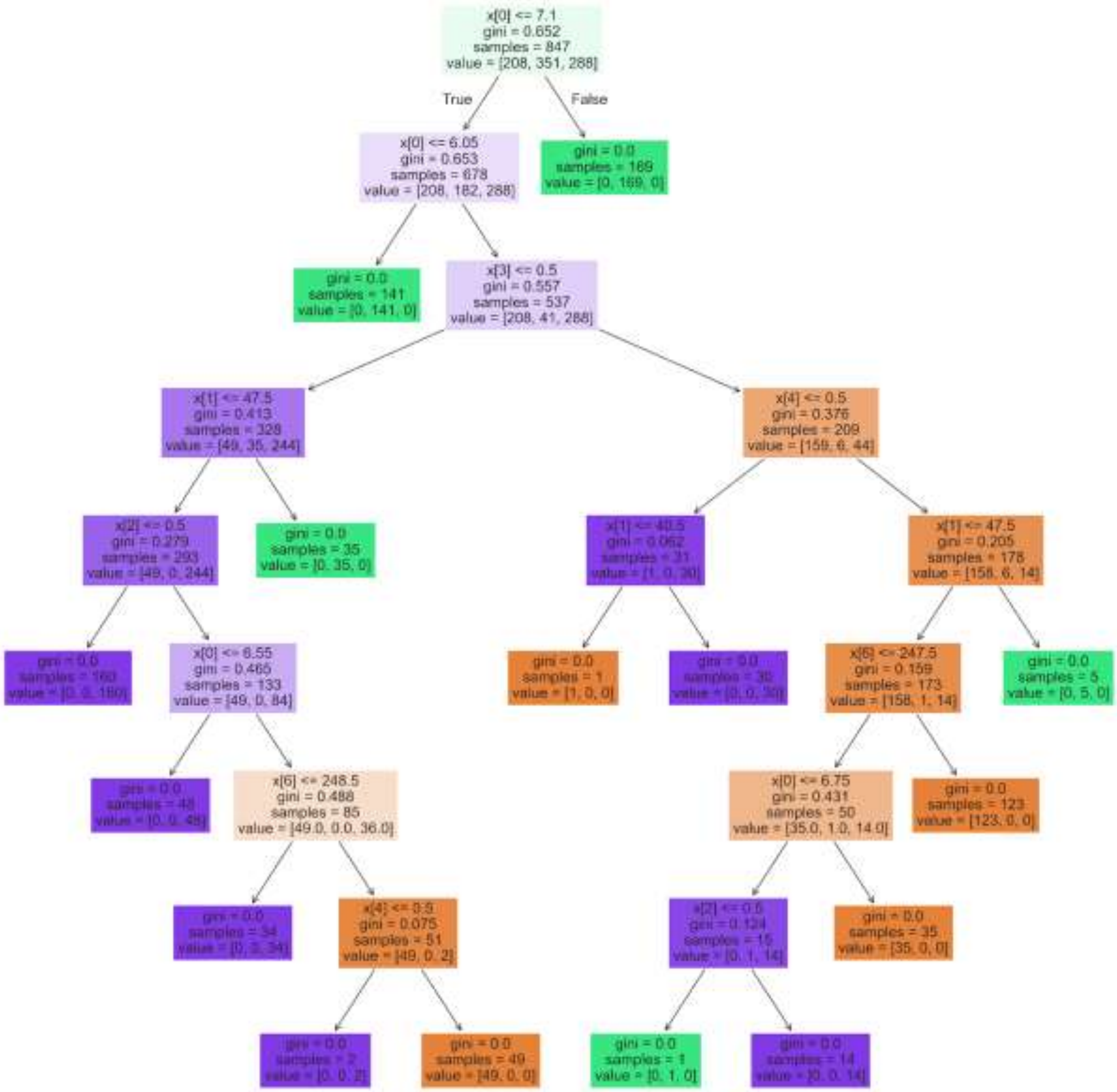


Figure 17: Decision tree model

3.1. pH is the primary decision driver (root node)

The decision tree places pH (x[0]) at the root node, indicating that it provides the most effective first-level separation among the samples. Although earlier hypothesis testing suggested that pH has only a weak linear relationship with Grade, the model uses pH as an initial screening mechanism rather than as a direct predictor of final quality. Samples with pH > 7.1 form a highly uniform branch dominated by Medium-quality outcomes, showing that unusually high pH levels represent a specific and stable subgroup. Conversely, samples with pH ≤ 7.1 require further analysis through additional critical-to-quality characteristics because they contain more variability. In practice, pH often acts as an early biological indicator of abnormality, detecting acidification, deterioration, or instability. Once these abnormal samples are filtered out, the remaining classification relies more heavily on sensory and thermal variables. Therefore, pH (x[0]) serves a crucial structural role by establishing the main pathways through which all subsequent splits occur.

3.2. Temperature is the secondary major split

After the initial separation by pH (x[0]), the model consistently uses Temperature (x[1]) as the next dominant splitting variable. Many high-quality branches form around specific thresholds, such as x[1] ≤ 47.5°C or x[1] ≤ 40.5°C, indicating that High-grade milk tends to occur within tightly controlled temperature bands. Meanwhile, branches representing Medium or Low grades typically correspond to wider, more unstable temperature ranges. This pattern confirms that thermal variation is a major driver of process inconsistency. Even when pH falls within acceptable limits, deviations in temperature can shift samples into lower-quality categories. As such, Temperature (x[1]) acts as the main operational critical-to-quality characteristic governing quality stability, reinforcing the need for strict thermal control in the production process.

Odor, Fat, and Turbidity are key sensory splitters: At deeper levels of the tree, the classification relies heavily on Odor (x[3]), Fat (x[4]), and Turbidity (x[5]), the critical-to-quality characteristics that determine the fine-grained quality distinctions:

Odor (x[3]) is consistently used to separate clean-smelling milk from samples showing sensory degradation. Acceptable odor patterns lead the model toward Medium or High nodes, whereas off-odor values direct samples toward Low quality.

Fat (x[4]) thresholds indicate the richness of the product. Lower fat levels (x[4] ≤ 0.5) often result in Medium or Low grades, while higher fat values support High-grade classifications due to improved sensory appeal.

Turbidity (x[5]) highlights physical stability: clearer samples (x[5] ≤ 0.5) typically correspond to High quality, while increased cloudiness reflects protein aggregation or contamination, which aligns with Low-grade outcomes.

These variables serve as classification refiners, discriminating between subtle differences in sensory performance once the broader structural divisions created by pH (x[0]) and Temperature (x[1]) have taken effect.

3.3. Colour contributes to distinguishing high vs medium

Although Colour (x[6]) does not drive major early-stage decisions, it appears repeatedly in the deeper splits that differentiate High from Medium quality. Colour thresholds, particularly around x[6] ≈ 248–255, help the model refine classifications within branches that are already close to High-grade conditions. More stable and higher colour values frequently align with High-quality leaf nodes. Thus, Colour (x[6]) functions as a secondary discriminator, enhancing the precision of the classification model without acting as a primary decision factor.

3.4. The tree shows a strong structure of quality polarization

The structure of the decision tree reveals clear signs of quality polarisation. Some branches form pure leaf nodes. For example, nodes containing exclusively High-quality samples, indicating stable and well-controlled process conditions. Meanwhile, other branches contain mixed distributions such as [50, 1, 14], showing that under certain combinations of critical-to-quality characteristics (e.g., specific ranges of pH, Temperature, and Turbidity), the process produces inconsistent outcomes. These mixed nodes highlight conditions that are sensitive to small variations, suggesting inadequate process control. This polarisation implies that while some quality pathways (especially those defined by pH (x[0]) and tight temperature ranges) are highly predictable, other pathways remain unstable and require targeted improvement.

4. Present results (Confusion Matrix, Accuracy, F1-Score)

4.1. Confusion Matrix

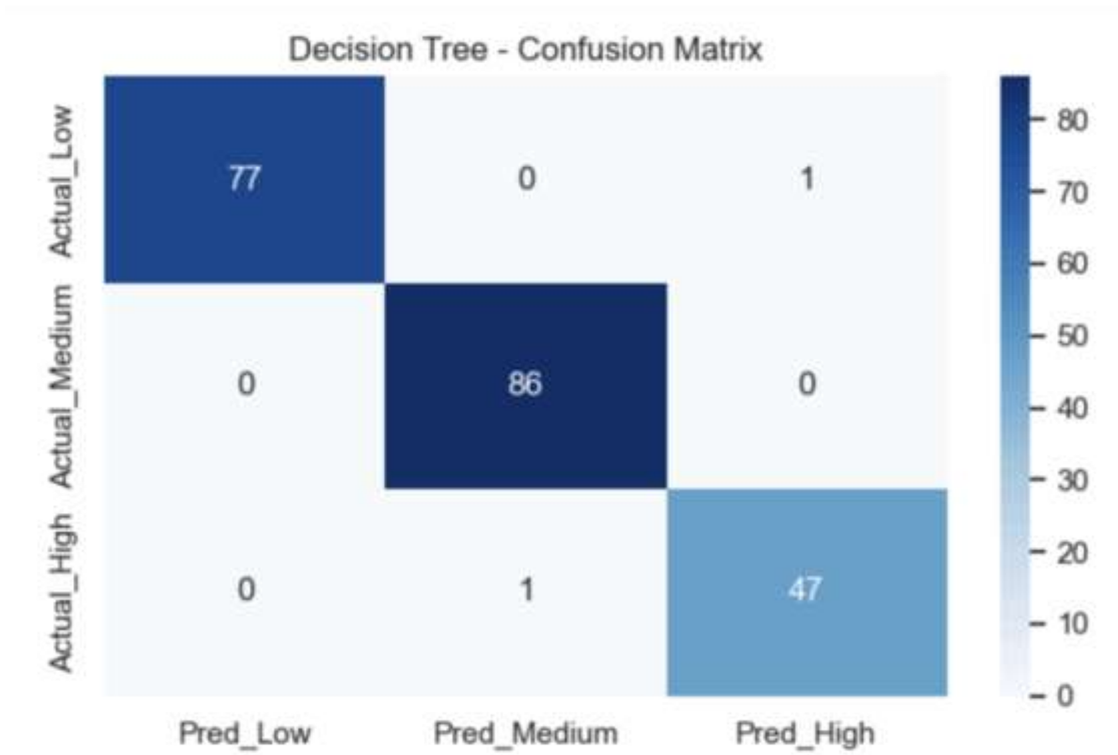


Figure 18: Decision tree - confusion matrix

The Confusion Matrix is a fundamental tool in evaluating classification models, providing insight into how well the model performs across different classes. In this case, the matrix shows the classification performance for milk quality, divided into three categories: Low, Medium, and High quality. The matrix is essential because it highlights both correct and incorrect classifications, giving a clear picture of how often the model misclassifies data.

From the results:

Low-quality milk: Out of 78 samples, 77 were correctly classified, while only 1 sample was misclassified as High-quality. This indicates that the model can differentiate between low and high-quality milk very well, with minimal confusion.

Medium-quality milk: All 86 samples in this category were classified correctly. This suggests that the model performs exceptionally well for medium-quality milk and has no trouble distinguishing it from the other two classes.

High-quality milk: For the 48 high-quality samples, 47 were correctly classified, with 1 misclassified as Medium-quality. Again, the misclassification occurs at the boundary, which is expected due to the similarities between medium and high-quality milk in terms of their features.

The misclassifications primarily occurred between Medium and High, as these two categories share overlapping characteristics. This slight misclassification is acceptable and reflects the inherent difficulty in differentiating between these two classes. However, overall, the model's performance is impressive, with only two incorrect predictions in total.

4.2. Accuracy & F1-Score

Accuracy: 0.9906

Classification Report:

	precision	recall	f1-score	support
0	1.0000	0.9872	0.9935	78
1	0.9885	1.0000	0.9942	86
2	0.9792	0.9792	0.9792	48
accuracy			0.9906	212
macro avg	0.9892	0.9888	0.9890	212
weighted avg	0.9906	0.9906	0.9906	212

Figure 19: Classification report

Accuracy is a simple metric that reflects the overall performance of the model by calculating the proportion of correct predictions to the total number of predictions. In this case, the Accuracy is 99.06%, meaning that the model correctly predicted the quality of milk in over 99% of the test samples. This high accuracy indicates that the model has learned to make reliable predictions based on the features provided.

F1-Score is a more comprehensive evaluation metric, as it balances precision (the proportion of true positives to predicted positives) and recall (the proportion of true positives to actual positives). The F1-score is particularly useful when dealing with imbalanced datasets, as it accounts for both false positives and false negatives.

The F1-scores for each quality category are as follows:

Low-quality milk: The model achieved an F1-score of 0.9935, indicating strong precision and recall. This suggests that the model not only correctly identifies the low-quality milk but also avoids misclassifying high-quality milk as low-quality.

Medium-quality milk: The F1-score for medium-quality milk is 1.0000, which is perfect. This means that the model has achieved flawless precision and recall for medium-quality samples.

High-quality milk: The F1-score for high-quality milk is 0.9792, which is also strong. Although not as high as the other two categories, it still indicates good performance and a minor issue with misclassifications, which was already discussed in the Confusion Matrix.

The macro average F1-score is 0.9890, which is a very good overall score, and the weighted average F1-score is 0.9906, showing that the model performs consistently well across all classes, with no class being underrepresented or poorly predicted.

4.3. Model Evaluation and Generalization

While the model demonstrates exceptional performance on the current dataset, it is crucial to evaluate its ability to generalize to new, unseen data. Overfitting is a common issue in machine learning models, especially when the dataset has clear, easily separable categories. Overfitting occurs when the model memorizes the training data rather than learning generalizable patterns, leading to high accuracy on the training set but poor performance on new data.

The high Accuracy and perfect F1-score for Medium-quality milk suggest that the model may have learned the specific characteristics of this class very well. However, to ensure the model performs well in real-world scenarios, where new data may introduce variability, further validation is necessary.

To assess the model’s generalization ability, the following steps are recommended:

K-fold cross-validation: This technique splits the dataset into multiple folds, training the model on one fold and testing it on the others. This helps evaluate how well the model generalizes across different subsets of data.

Pruning the decision tree: Pruning helps reduce the complexity of the model, ensuring it doesn't overfit the data by cutting back unnecessary branches in the decision tree.

Testing on new production batches: This would test the model's ability to classify milk quality from different production cycles, ensuring that it works well across a range of real-world conditions.

In conclusion, while the model performs exceptionally well within the current dataset, it is essential to validate it further through cross-validation, pruning, and testing on new data before deploying it in a live production environment.

VI. Management and quality improvement proposals

1. Rationale for Using the DMAIC Framework

DMAIC is chosen for three main reasons:

The production problems are complex and multi-factor: Temperature, Odor, Turbidity, and Fat interact strongly. DMAIC supports advanced statistical tools (ANOVA, Chi-Square, SPC, Cp/Cpk) that are necessary to understand these relationships accurately.

A data-driven approach is required: The company needs measurement, evaluation, and statistical confirmation to understand the actual behavior of the process. DMAIC is specifically designed for processes where data must guide decisions.

The company must not only improve but also sustain improvements: DMAIC includes a formal Control phase, which is essential for maintaining improvements and preventing the process from returning to its previous unstable condition.

For these reasons, DMAIC is the most appropriate and effective approach for guiding process improvement at Happy Cow Ltd.

2. How the DMAIC Framework was applied

2.1. Define phase (Sections I and II)

The problem was defined as a high percentage of Low-grade milk (around 40.5%) and unstable production performance. The business need is to produce consistent high-grade milk to meet the requirements of premium markets.

2.2. Measure phase (Section III)

Section III measured the current process performance by analyzing the distribution and variation of Temperature, Odor, Turbidity, Fat, Colour, and pH. Grade distribution results also provided a baseline for improvement.

2.3. Analyze phase (Sections IV and V)

Root causes were explored using ANOVA, Chi-Square tests, correlation analysis, SPC (X-bar and R charts), process capability indices, and the Decision Tree model. Temperature was identified as the strongest CTQ, followed by Odor, Turbidity, Fat, and Taste. The Decision Tree achieved **99.06% accuracy**, confirming that these CTQs reliably determine product quality.

2.4. Improve phase

The Improve phase is organized into three main areas: Input Control, Process Control, and Output Control because the Analyze phase showed that these areas contain the main sources of variation.

2.4.1. Improvements in Input Control

Raw Milk Acceptance Standards: Set clear acceptance limits for pH, Odor, Turbidity, and Fat. Use simple rapid-test kits and digital recording to ensure consistent raw milk quality.

Supplier Performance Management: Create a Supplier Scorecard to review supplier performance monthly. Suppliers that repeatedly fail to meet standards should receive corrective action plans or training.

Storage and Handling Improvements: Apply immediate chilling, proper tank sanitation, and first-in–first-out (FIFO) practices. These steps reduce contamination and prevent early deterioration of milk.

Table 1: Feasibility of Input Control Actions

Improvement Action	Cost Level	Implementation Difficulty	Notes
Raw Milk Acceptance Standards	Low	Easy	Quick tests and digital logs are inexpensive.
Supplier Scorecard	Low	Easy–Moderate	Mainly administrative work; no new equipment needed.
Storage & Handling (FIFO, cleaning logs, chilling)	Low–Moderate	Easy	Uses existing equipment; changes are mostly procedural.

2.4.2. Improvements in Process Control

Temperature Control: As Temperature was the most critical CTQ, install PID temperature controllers, reliable sensors, and alarms to keep Temperature in the 38–42°C range. Weekly SPC chart reviews should be used to detect early variation.

Standard Operating Procedures (SOPs): Develop or update SOPs for heating, cooling, cleaning, and deviation response. Regular training ensures that all operators follow procedures consistently.

Real-Time Monitoring: Use a digital dashboard to track Temperature, Odor, Turbidity, and Fat in real time. Continuous data logging supports both immediate decision-making and future improvement cycles.

Table 2: Feasibility of Process Control Actions

Improvement Action	Cost Level	Difficulty	Notes
PID Temperature Controllers	Moderate	Moderate	Most expensive action but crucial for quality.
SOP Updates & Training	Low	Easy	Requires time, not money.
Real-Time Monitoring Dashboard	Low–Moderate	Moderate	Can be built using simple tools; sensors may add minor cost.

2.4.3. Improvements in Output Control

Predictive Model Integration: The Decision Tree developed in Section V achieved **99.06% accuracy**, with almost perfect classification across Low, Medium, and High-quality categories. This performance is strong enough to support operational decision-making. The model uses seven key variables: pH, Temperature, Odor, Fat, Turbidity, Taste, and Colour, to classify batches objectively.

Low-quality batches: Low-quality batches should not be distributed to premium or standard markets in their current form. Instead, the recommended actions are: **Reprocess the batch** to correct quality defects whenever possible; or **send to lower-tier / secondary markets** where quality requirements are less strict and product usage is more flexible. These batches often indicate significant upstream issues, so trends in Low-quality predictions should trigger investigations into raw milk quality, temperature control, or sanitation practices.

Medium-quality batches: Medium-quality batches may be: **Released only to standard markets**, not premium ones; and **Recorded and monitored closely** because a rising number of Medium-quality outputs often signals early process drift.This allows the factory to maintain brand reputation while still minimizing product waste.

High-quality batches: High-quality batches should: **Be approved for premium markets**, and have their quality characteristics stored as **benchmark profiles** for future optimization. Tracking High-quality patterns can help the company understand which operating conditions consistently produce the best outcomes.

Final Inspection Procedure: Combine model predictions with sensory evaluation to make consistent decisions about whether a batch should be accepted, reprocessed, downgraded, or rejected.

Table 3: Feasibility of Output Control Actions

Improvement Action	**Cost Level**	**Difficulty**	**Notes**
Decision Tree Model Integration	Very Low	Easy	Requires basic software setup and staff training; improves consistency in output decisions.
Standardized Final Inspection	Low	Easy	Only requires procedure writing and training.

2.5. Control phase

The Control phase ensures that improvements are maintained and that the process does not return to its previous unstable condition.

2.5.1. Key Performance Indicators (KPIs)

- KPIs should be monitored regularly to evaluate process performance:
- Percentage of Temperature readings within 38–42°C
- Percentage of High-grade batches
- Supplier compliance rate
- Reduction in process variation
- Frequency of deviations and reprocessing events

These KPIs directly connect back to the problems identified in the Define and Measure phases.

2.5.2. Routine Monitoring and Audit Activities

- **Weekly:** SPC chart review for Temperature and other CTQs
- **Monthly:** Supplier performance review and quality meetings
- **Quarterly:** SOP updates and sanitation audits
- **Annually:** Equipment calibration and process capability review (Cp, Cpk)

These activities establish discipline and prevent the recurrence of defects.

2.5.3. Continuous Learning and Prevention of Recurrence

Whenever a deviation or defect occurs, the company should apply root-cause analysis tools such as the 5 Whys or the Fishbone diagram. Lessons learned must be included in SOP updates, training programs, and preventive actions. Encouraging small improvement ideas (Kaizen activities) supports a culture of continuous learning.

VII. Conclusion and recommendations

1. Conclusion

The findings of this study show that Happy Cow's milk production process is not yet stable or capable enough to support the company's strategic goal of expanding into premium markets. The analysis revealed substantial variation in the most critical-to-quality variables, especially Temperature and pH, which consistently drive whether milk becomes Low, Medium, or High in quality. This instability explains the high number of Medium- and Low-quality outputs and demonstrates that the current process does not fully meet the requirements for higher-value market segments.

2. Recommendations

Based on the findings of this study, several priority actions are recommended to help Frodo improve the production process and achieve greater quality stability.

First, the factory should apply strict control over **Temperature,** as this CTQs were shown to have the strongest impact on final product quality. Installing reliable sensors, alarms, and enforcing tighter acceptance limits will significantly reduce process variation.

Second, Frodo should invest in an **automated data collection and real-time monitoring system** to continuously track key variables such as Temperature, pH, Odor, Fat, Turbidity, and Colour. This will improve decision-making and allow for early detection of process drift.

Third, the company should integrate the **Decision Tree predictive model** into the final inspection stage. With a demonstrated accuracy of 99.06%, the model can support consistent and objective classification of milk batches, ensuring that High-quality products are directed to premium markets, Medium-quality batches to standard markets, and Low-quality batches are either reprocessed or sent to lower-tier markets.

Finally, Frodo should prioritize the full deployment of the **DMAIC continuous improvement cycle** to guide long-term quality enhancement. DMAIC will enable the factory to identify root causes systematically, implement effective corrective actions, and maintain improvements through routine monitoring and KPI tracking.

Together, these recommendations provide a practical and sustainable roadmap for achieving higher process capability and consistent product quality.