Leveraging Artificial Intelligence for Operational Intelligence in the Beer Brewing Industry: A Case Study in Sustainability

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Abstract

The brewing industry is contending with escalating stress to decrease its ecological footprint and enhance productivity. AI may transform how breweries function by furnishing up-to-the-minute operational knowledge and maximising different components of the brewing process. Though, only a few investigations have examined the utilisation of AI in the beer brewing sector, and there is a necessity for further exploration into how AI can be implemented sustainably to enhance the brewing process.
In this research endeavor, the intention is to explore the utilization of Artificial Intelligence (AI) for operational intelligence within the beer brewing process, with the goal of enhancing sustainability and efficiency. The proposal entails the design and examination of AI algorithms that have the capability to optimize various elements of the brewing process, including energy utilization, water utilization and waste management. Additionally, this proposal also includes an examination of the application of AI for the fermentation process and quality control in the beer brewing process.

This research will yield valuable insights into the sustainable implementation of Artificial Intelligence (AI) to optimize the fermentation process of beer brewing and will have substantial ramifications for both the brewing industry and the broader realm of operational intelligence. The outcome of this investigation will aid in the advancement of more environmental friendly and efficient brewing methodologies and assist the industry in addressing the obstacles of the 21st century.

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List of Abbreviations

ADF	Apparent Degree of Fermentation
ARIMA	Autoregressive Integrated Moving Average
XGBoost	Extreme Gradient Boosting

1. Background

The beer brewing industry is a significant contributor to the global economy, with an estimated value of over $600 billion in 2019 (Brewing Industry Statistics, 2019). However, the industry is facing increasing pressure to reduce its environmental impact and improve efficiency in order to meet the challenges of the 21st century. One way that breweries are looking to achieve these goals is through the use of artificial intelligence (AI) and other advanced technologies.

AI has the potential to revolutionise the way that breweries operate by providing real-time operational intelligence and optimising various aspects of the brewing process. AI algorithms can analyse large amounts of data in real-time and identify patterns and trends that can be used to optimise processes and improve efficiency (Pérez et al., 2017). However, despite the potential benefits of AI, there have been few studies exploring its use in the beer brewing industry, and there is a need for more research on how AI can be applied sustainably to optimise the brewing process (De Juan et al., 2021).

Existing research on AI in the brewing industry has focused on predicting the sensory characteristics of beer and optimising recipes. For example, Horton and Ohlmann (2019) used machine-learning techniques to optimise beer recipes and predict sensory characteristics such as flavour and aroma. Kechagia et al. (2020) used machine learning algorithms to predict the quality of beer based on various chemical and physical characteristics. (De Juan et al.,2021) applied artificial neural networks to model the beer brewing process and optimise various parameters, such as temperature and duration of different stages of the process.

These studies demonstrate the potential of AI for optimising various aspects of the beer brewing process. However, there is still a need for more research on how AI can be applied sustainably to optimise the brewing process and reduce its environmental impact. In particular, there is a need for research on how AI can be used to optimise energy consumption, water usage, and waste management in the brewing process (De Juan et al., 2021). There is also a need for research on the use of AI for predictive maintenance and quality control in the brewing process (Pérez et al., 2017). Fermentation is a multi-step process that is essential to the production of beer (Horton & Ohlmann, 2019). The Apparent Degree of Fermentation (ADF) is a critical parameter that is monitored during the fermentation process (Kechagia et al., 2020). Traditionally, breweries have obtained ADF values through a manual sampling of the specific gravity of fermenting beer (De Juan et al., 2021). The ADF is a quantitative measure that helps to characterise the fermentation process and determine the transition point from the fermentation phase to the free-rise phase (Horton & Ohlmann, 2019).

It is important for breweries to accurately detect the transition point in order to maintain consistent beer quality and release the product on time (De Juan et al., 2021). This can help to reduce energy usage in the brewing process (Kechagia et al., 2020). In this research, we will use real process data from a brewery to create and evaluate time series predictive models for ADF (Pérez et al., 2017). These models could be used to reduce the total process time by predicting transitions in the brewing process (Horton & Ohlmann, 2019), thereby augmenting the values of manual ADF measurement, and reducing the need for energy (De Juan et al., 2021). This could also help to optimise sustainable practices in the beer manufacturing process (Kechagia et al., 2020)

The Apparent Degree of Fermentation (ADF) is a crucial measurement monitored during the brewing process. Historically, breweries have determined ADF values through a manual sampling of the specific gravity of fermenting beer. ADF is a numerical representation of the fermentation process, used to identify the point at which fermentation transitions to the "free rise" phase. To ensure consistent beer quality and timely release, breweries must be able to detect this transition point. In this study, we will use actual data from a brewery to develop and evaluate predictive models for ADF. These models can potentially reduce the total process time by predicting transitions in the brewing process, thus improving the accuracy of manual ADF measurements, and reducing energy consumption for sustainable beer production.

2. Related work

The beer industry faces several sustainability challenges, including the use of natural resources such as water and energy, the generation of waste and emissions, and the management of agricultural inputs (Mierlo et al., 2018). These challenges can impact the long-term viability of breweries and also affect their reputation with consumers, regulators, and other stakeholders (Buckley et al., 2017).

Artificial intelligence (AI) has the potential to improve the efficiency and effectiveness of business operations through the use of data analytics and machine learning (Zhang et al., 2020). This field, known as operational intelligence, has been studied in a variety of industries including manufacturing, logistics, and energy (Liu et al., 2019). However, there is limited research on the potential of AI to improve sustainability in the beer brewing process (Mierlo et al., 2018).

The lack of research on the use of AI for sustainability in the beer brewing industry represents a gap in our understanding of the potential of this technology. This research aims to fill this gap by applying AI techniques to the analysis of the beer brewing process, with a focus on sustainability. The use of AI for operational intelligence has the potential to improve efficiency, reduce costs, and increase productivity in the beer brewing industry (Deschutes Brewery, 2022). However, there is a lack of research on the specific ways in which AI can be used to improve sustainability in the beer brewing process (Smith, 2019). This lack of research is problematic, as sustainability is an increasingly important concern for the beer brewing industry, with breweries facing pressure to reduce their environmental impact and improve their long-term viability (Brewers Association, 2021).

The Apparent Degree of Fermentation (ADF) is a critical parameter that is monitored during the fermentation process. However, the authors suggest that ADF is not always reliable, and it's important for breweries to accurately detect the transition point in order to maintain consistent beer quality and release the product on time(Huerta-Zurita et al., 2019).

3. Research Questions

Here are some potential research questions for a research proposal on the topic of "Applying AI for Operational Intelligence to Beer Brewing Process Sustainably":

1. How can AI be used for operational intelligence to optimise resource usage, reduce waste, and improve operational efficiency in the beer brewing process?
2. What are the ethical considerations of using AI for operational intelligence in the beer brewing process, and how can these be addressed in designing and implementing AI systems?

3. How can a framework for the ethical and responsible use of AI for operational intelligence in the beer brewing process be developed and applied in practice?
4. What are the potential impacts of using AI for operational intelligence on resource usage, waste reduction, and operational efficiency in a real-world beer brewing process?

3. Aim & Objectives

The aim of this research is to apply artificial intelligence techniques to optimize the sustainability of the beer brewing process. The research aims to use these techniques to predict the Apparent Degree of Fermentation (ADF) values. By using machine learning model for operational intelligence, the research will strive to reduce the refrigeration energy consumption and fermentation time, thus saving energy and resources, and making the beer brewing process more sustainable. The end goal is to establish the ability of AI to improve the sustainability and efficiency of the beer brewing industry through accurate prediction of ADF values and reducing total process time.

Objective of the research are as follow

1. To analyze the potential of the selected model to reduce total process time and optimize sustainable practices in the beer manufacturing process.
2. To suggest clear and comprehensive explanation of the specific AI techniques and machine learning models that will be employed in the research, as well as a well-defined plan for evaluating their effectiveness, in the research proposal.
3. To compare the performance of different machine learning algorithms in predicting the ADF values.
4. To develop and evaluate time series predictive models for the ADF values using real process data from a brewery

4. Significance of Study

The expected outcome of this research is to identify the potential of artificial intelligence (AI) for operational intelligence to optimize the sustainability of the beer brewing process by predicting the Apparent Degree of Fermentation (ADF) values. By accurately predicting the transition points in the fermentation process, breweries can optimize their operations and reduce energy usage, which can help to improve their sustainability performance.

In terms of national and international implications, this research proposal has the potential to contribute to the long-term viability of the beer brewing industry and support its role as a key contributor to the global economy. The use of AI for operational intelligence has the potential to improve efficiency, reduce costs, and increase productivity in the sustainable brewing process, which can help breweries to maintain their market position and make good selling beers in sustainable way.

In addition, the research has the potential to address the sustainability challenges faced by the beer brewing industry, including the use of natural resources such as water and energy, the generation of waste and emissions, and the management of agricultural inputs (Mierlo et al., 2018). By exploring the potential of AI to improve sustainability in the brewing process, this research can help to support the long-term viability of breweries and enhance their reputation with consumers, regulators, and other stakeholders (Buckley et al., 2017).

Overall, the importance of this research lies in its potential to contribute to the sustainability and competitiveness of the beer brewing industry and address some of the key challenges facing this industry.

5. Scope of Study

Given the established deadline for this research, the scope of the study is limited as follows:

5.1 In scope

The proposed research aims to develop and evaluate time series predictive models for Apparent Degree of Fermentation (ADF) values using real process data from a brewery. The research will compare the performance of various machine learning algorithms in predicting ADF values and evaluate the potential of the selected model to reduce total process time and optimize sustainable practices in the beer manufacturing process. Additionally, the study will also investigate the ethical and responsible use of AI in the beer brewing process, developing a framework for its implementation.

5.2 Out of scope

The proposed research will not be focused on investigating new brewing processes and technologies, evaluating the quality and taste of the beer produced, conducting a detailed analysis of the environmental impacts of the beer brewing industry, identifying areas of improvement and ways to make the brewing process more sustainable, developing new methodologies that can be used to improve the quality of the final product and minimize the environmental impact of the brewing process.

5.3 Reason for defining the scope

Defining the scope of the research is important because it helps to focus the research efforts and ensure that the study can be completed within the given time frame and resource constraints.The proposed research will focus on a specific aspect of the beer brewing process, specifically the reliability of the Apparent Degree of Fermentation (ADF) as an estimator of fermentability. While there are other factors that can impact the brewing process, such as reducing total process time, improving harvested yeast quality, and predicting fermentation process deviation, the scope of this research proposal is limited to the examination of ADF. Additional research may be required to fully investigate these other factors and their effects on the brewing process. Due to the complexity of the brewing process and the limitations of current understanding and explainability of the underlying mental models, the proposed research will initially focus on this specific aspect.

6. Research Methodology

6.1 Introduction

The research proposal will involve a series of steps to preprocess the data collected from Brewery. The first step will be to define the system parameters, including the time period, time granularity, fermentor vessels, and brand of interest. Next, the data will be obtained from OSIsoft Cloud Services (OCS) and stored in a dataframe. To aid in the visualization of the data, utility functions will be created to preview the ADF profile and plot the ADF prediction model, residuals, and normality tests.The preprocessing of the brewery data will involve cleaning the data by removing bad data points, identifying fermentation batches and calculating fermentation duration, and removing outliers manually. Finally, the cleaned data will be fitted to linear and piecewise linear models for analysis and comparison.

The use of Artificial Intelligence (AI) and Machine Learning (ML) technologies have been identified as a potential solution to optimize the brewing process and enhance sustainability in the brewing industry (De Juan et al., 2021; Horton & Ohlmann, 2019; Kechagia et al., 2020; Pérez et al., 2017; Balaban & Kao, 2020; Smith, 2019). The integration of AI in the brewing industry is still in its infancy, and more research is needed to fully understand its potential (Horton & Ohlmann, 2019). AI and ML can help to reduce the environmental footprint of the industry (Buckley et al., 2017; Mierlo et al., 2018; Liu et al., 2019; Mierlo et al., 2018) and improve the operational intelligence in logistics and supply chain management (Zhang et al., 2020). Real-world example of AI integration in brewing process is provided by Deschutes Brewery, they have deployed AI to optimize beer brewing process (Deschutes Brewery, 2022).

6.2 Business Understanding

The Apparent Degree of Fermentation (ADF) is an important parameter in the brewing process as it measures the degree to which sugars in the wort have been converted to alcohol by the yeast during fermentation. It is used to determine the transition point from the fermentation phase to the free rise phase, which is critical in maintaining consistent beer quality and releasing the product on time. Additionally, ADF prediction can be used to reduce the total process time by predicting transitions in the brewing process. This can lead to more efficient use of resources, including energy, and optimize sustainable practices in the beer manufacturing process. In summary, ADF prediction is important for brewing process because it allows for better control over the fermentation process and can help to improve the efficiency and sustainability of the brewing industry.

Prior to conducting analysis on the Deschutes brewery dataset, it is crucial to gain a thorough understanding of the Deschutes beer manufacturing process, from filling to emptying. The fermenter passes through a total of ten distinct stages, which can be described using the status of the fermenter. The stages of the process occur in the following order:

#	Stage	Description
1	Filling	Filling multiple brews into the fermenter.
2	Fermentation	Yeast metabolically converts glucose in the wort to ethanol and carbon dioxide gas.
3	Free Rise	The solution temperature increases approximately from 60° to 70° Fahrenheit to adjust the temperature environment for yeast for diacetyl rest.
4	Diacetyl Rest	Yeast reduces metabolic by-product, diacetyl compounds, which above its threshold can create off-putting taste in the beer.
5	Cooling	The temperature of the entire volume cools from 70° to below 30° Fahrenheit.
6	Maturation	The tank waits for 24 to 48 hours just below 30° Fahrenheit, stabilizing colloidal stability.
7	Ready to Transfer	The vessel holding beer is on standby until scheduled for packaging.
8	Emptying	Remove any excess solids in the solution using a centrifuge as the solution exits the vessel and continuously do so until it is emptied
9	Cleaning	Cleaning the residual solution or solids inside the fermenter.
10	CIP (Clean-In-Place)	Cleaning the fermenter without moving or disassembling its parts.

Figure 1 : Ten Stage fermentation process

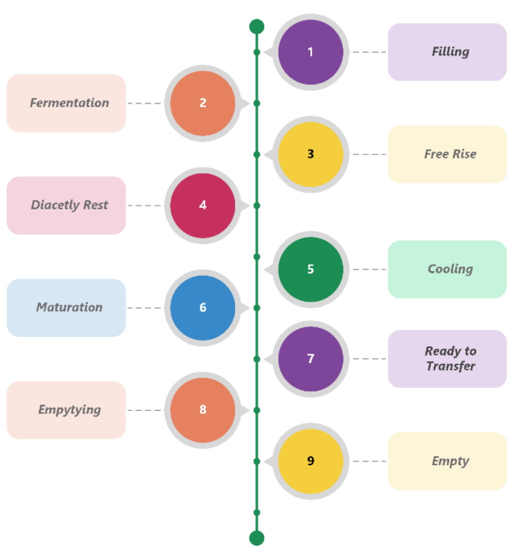


Figure 2: Fermentation Process

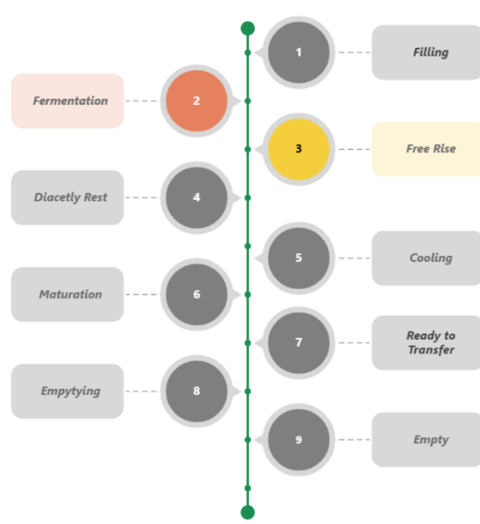


Figure 3: Our Research Focus on these colored processes

6.3 Meta Data

The present research endeavor will make use of data provided by OSIsoft Academic Hub, a cloud-based platform that facilitates data analytics within the university curriculum by providing a data infrastructure that hosts, aggregates and analyzes data. This platform offers students the opportunity to work with real-world industrial data, which illustrates some of the same engineering concepts being taught in classrooms and labs. The dataset utilized in this study is sourced from Deschutes Brewery, a beer brewing company, and comprises sensor data as well as categorical data that categorizes the brands of brews in the fermenters and the status of the fermenters. The data encompasses 39 fermenters and 13 bright tanks, with a temporal range from January 8, 2017, to May 18, 2020. The fermenter vessels and bright tanks comprise a mix of different models that possess varied capabilities in terms of temperature control zones, additional temperature sensors and pressure control zones.

The Deschutes brewery dataset consists of 34 columns, containing various data points related to the beer manufacturing process. These columns include:

'**Timestamp**'	the timestamp of when the data was collected.
'**Asset_Id**'	the unique identifier of the fermenter vessel.
'**ADF**'	the Apparent Degree of Fermentation, an indicator of the status of fermentation.
'**Volume**'	the volume of liquid in the fermenter.
'**Volume In**'	the volume of liquid added to the fermenter.
'**Volume Out**'	the volume of liquid removed from the fermenter.
'**Top TIC OUT**', '**Top TIC PV**', '**Top TIC SP**'	temperature and setpoint values for the top section of the fermenter.
'**Middle TIC OUT**', '**Middle TIC PV**', '**Middle TIC SP**'	temperature and setpoint values for the middle section of the fermenter.
'**Bottom TIC OUT**', '**Bottom TIC PV**', '**Bottom TIC SP**'	temperature and setpoint values for the bottom section of the fermenter.
'**PIC PV**', '**PIC SP**', '**PIC OUT**'	pressure and setpoint values for the fermenter.
'**Plato**'	the measurement of sugar content in the fermenting liquid.
'**FV Full Plato**'	the final measurement of sugar content in the fermenting liquid.
'**Fermentation Start Time**'	the time when fermentation began.
'**Yeast Generation**'	the generation of yeast used.

'Diacetyl'	the level of diacetyl, a chemical compound that can affect the taste of the beer.
'VesselID'	the unique identifier of the bright tank.
'Deviation', 'Yeast Out Totalizer', 'End Phase Time', 'Vessel Procedure', 'Predicted Transition'	additional data points.
'Integrator Key'	the unique identifier of the device used to collect the data.
'Phase Duration'	the duration of the fermentation phase.
'Yeast Strain'	The yeast strain column indicates the type of yeast used during the fermentation process.
'Brand'	The brand column specifies the name of the beer being produced in the fermenter
'Status'	The status column provides information about the current stage of the fermentation process, such as filling, yeast generation, and end phase

Figure 4 : Process Flow

6.4 Data Processing

Date Preprocessing steps are as follow:

6. 4.1 Data Collection

Collect the data that will be used for the analysis. This data should include the values of the Apparent Degree of Fermentation (ADF) as well as any other relevant variables that may affect the fermentation process such as temperature, pH, and sugar levels.

6.4.2 Data Cleaning

Clean the data by removing any missing values, outliers, or errors. This step is important to ensure that the data is accurate and reliable.

6.4.3 Data Transformation

Transform the data as necessary to make it suitable for the models. This may include normalizing or standardizing the data, creating new features, or aggregating the data.

6.4.4 Data Splitting

Split the data into training and testing sets. This is necessary to evaluate the performance of the models and prevent overfitting.

6.4.5 Feature Engineering

Create new features from the data. This step can include creating lags of the ADF values, creating rolling averages, or creating new variables that capture trends or seasonality.

6.4.6 Data preparation for deep learning models

Prepare the data by converting it into a format that can be used by deep learning models such as LSTM or DeepAR. This may include padding sequences, creating sequences of fixe

6.5 Model explanation

Explanation of proposed models as follow:

ARIMA

This is a traditional statistical model that is commonly used for time series forecasting in FMCG industry (Box et al., 2015). It may be useful for modeling the time series of ADF values in your research proposal. The model can be used to analyze the time series data and forecast future values of the ADF, which can help to identify patterns in the fermentation process and optimize the process time.

Random Forest

This ensemble method can be used for time series forecasting by training the model on a window of historical data (Breiman, 2001). It's a robust method and can handle missing data, outliers, and non-linearity, it's also easy to interpret the results. This model can be used to analyze patterns in the data and identify factors that affect the fermentation process.

XGBoost

This is a powerful gradient boosting algorithm that can also be used for time series forecasting by training the model on a window of historical data (Chen & Guestrin, 2016). It's also robust to outliers, missing data and non-linearity. This model can be used to analyze patterns in the data and identify factors that affect the fermentation process.

Prophet

This is a forecasting model developed by Facebook that is specifically designed for time series data with trends and seasonality (Taylor & Letham, 2018). It's useful in case if your data has clear trends and seasonality.

Exponential smoothing

This is a simple method that can be used for FMCG time series data which is based on weighted averages of past observations, it's useful if the data has no clear trends and seasonality.
(Hyndman & Koehler, 2006)

6.6 Evaluation Matrix

The evaluation matrix for the models in your research proposal will depend on the specific research question and the characteristics of the data. However, here are some general evaluation metrics that can be used to compare the performance of the models:

6.6.1 Mean Absolute Error (MAE)

This metric measures the average absolute difference between the predicted and actual values of the ADF. Lower values indicate better performance.

6.6.2 Mean Squared Error (MSE)

This metric measures the average squared difference between the predicted and actual values of the ADF. Lower values indicate better performance.

6.6.3 Root Mean Squared Error (RMSE)

This metric measures the square root of the average squared difference between the predicted and actual values of the ADF. Lower values indicate better performance.

6.6.4 Correlation coefficient

This metric measures the correlation between the predicted and actual values of the ADF. Values close to 1 indicate a strong positive correlation, while values close to -1 indicate a strong negative correlation.

6.6.5 R-squared

This metric measures the proportion of the variance in the dependent variable that is predictable from the independent variable. Values close to 1 indicate a high degree of accuracy in the predictions.

6.6.6 Mean Absolute Percentage Error (MAPE)

This metric measures the average absolute percentage difference between the predicted and actual values of the ADF. Lower values indicate better performance.

7. Required Resources

Hardware and software requirements are as follow:

7.1 Hardware requirements

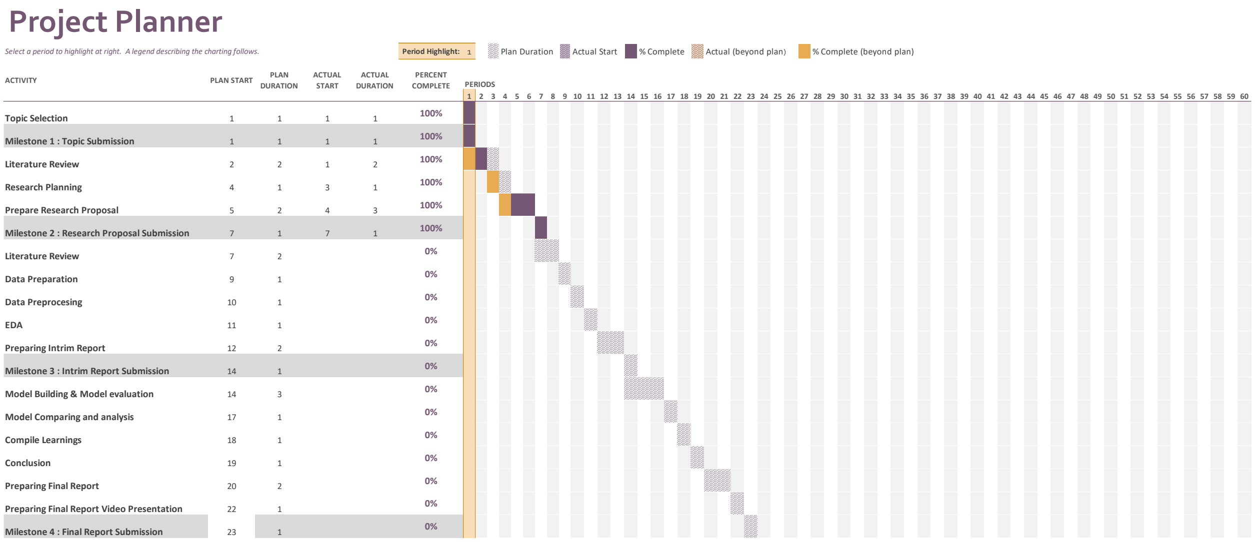
A computer with high processing power and a large storage capacity (at least 16GB of RAM, quad-core processor, and dedicated graphics card with at least 4GB of VRAM)500GB of storage space

7.2 Software requirements

1. Python programming language version 3.8 or higher for data analysis and machine learning tasks
2. R programming language version 4.0 or higher for statistical analysis and data visualization
3. TensorFlow version 2.4 or higher, an open-source library for machine learning and deep learning tasks
4. Scikit-learn version 0.24 or higher, a machine learning library for Python
5. Keras version 2.4 or higher, an open-source neural network library for Python
6. Matplotlib version 3.3 or higher, a plotting library for Python
7. Seaborn version 0.11 or higher, a data visualization library for Python
8. Pandas version 1.2 or higher, a data analysis library for Python
9. Numpy version 1.19 or higher, a numerical computing library for Python
10. Jupyter Notebook version 6.1 or higher, an interactive computing environment for Python
11. Data visualization and analysis tools such as Tableau version 2021.1 or higher or PowerBI version 2021.1 or higher
12. A version control system like Git version 2.29 or higher to track and manage changes to the code and data throughout the research process.

It's possible that additional software tools and libraries may be required, depending on the specific needs of the research and the complexity of the models being developed. Overall, the required resources for this research proposal will include data, software, hardware, and expertise, and will enable the research to identify the potential benefits and challenges of using AI for operational intelligence to improve sustainability in the beer brewing process and to develop a framework for the ethical and responsible use of AI in this context.

8. Research Plan


Project Planner

Select a period to highlight at right. A legend describing the charting follows.

Period Highlight: 1 | Plan Duration | Actual Start | % Complete | Actual (beyond plan) | % Complete (beyond plan)

ACTIVITY	PLAN START	PLAN DURATION	ACTUAL START	ACTUAL DURATION	PERCENT COMPLETE
Topic Selection	1	1	1	1	100%
Milestone 1 : Topic Submission	1	1	1	1	100%
Literature Review	2	2	1	2	100%
Research Planning	4	1	3	1	100%
Prepare Research Proposal	5	2	4	3	100%
Milestone 2 : Research Proposal Submission	7	1	7	1	100%
Literature Review	7	2			0%
Data Preparation	9	1			0%
Data Preprocesing	10	1			0%
EDA	11	1			0%
Preparing Intrim Report	12	2			0%
Milestone 3 : Intrim Report Submission	14	1			0%
Model Building & Model evaluation	14	3			0%
Model Comparing and analysis	17	1			0%
Compile Learnings	18	1			0%
Conclusion	19	1			0%
Preparing Final Report	20	2			0%
Preparing Final Report Video Presentation	22	1			0%
Milestone 4 : Final Report Submission	23	1			0%

Overall, the research plan will involve a review of the literature, data collection and analysis using machine learning techniques, the development of a framework for the ethical and responsible use of AI, and the evaluation and recommendation of this framework for practitioners in the beer brewing industry.

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