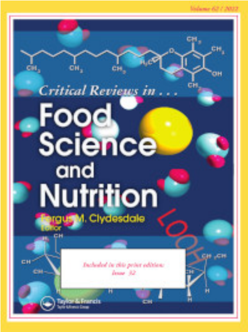

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REVIEW

Artificial intelligence-based approaches for traditional fermented alcoholic beverages' development: review and prospect

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ABSTRACT
Traditional fermented alcoholic beverages (TFABs) have gained widespread acceptance and enjoyed great popularity for centuries. COVID-19 pandemics lead to the surge in health demand for diet, thus TFABs once again attract increased focus for the health benefits. Though the production technology is quite mature, food companies and research institutions are looking for transformative innovation in TFABs to make healthy, nutritious offerings that give a competitive advantage in current beverage market. The implementation of intelligent platforms enables companies and researchers to gather, store and analyze data in a more convenient way. The development of data collection methods contributed to the big data environment of TFABs, providing a fresh perspective that helps brewers to observe and improve the production steps. Among data analytical tools, Artificial Intelligence (AI) is considered to be one of the most promising methodological approaches for big data analytics and decision-making of automated production, and machine learning (ML) is an important method to fulfill the goal. This review describes the development trends and challenges of TFABs in big data era and summarize the application of AI-based methods in TFABs. Finally, we provide perspectives on the potential research directions of new frontiers in application of AI approaches in the supply chain of TFABs.

KEYWORDS
Traditional fermented alcoholic beverages; artificial intelligence; big data; fermentation regulation; microbial community

Introduction

Traditional fermented alcoholic beverages (TFABs) is alcoholic drinks originated from microbial metabolisms (bacteria, yeasts, molds, etc.) that transform raw materials to ethanol and other metabolites (Cong, Hai, and Yan 2017; Wedajo Lemi 2020). Archaeologists found a dozen of pottery jars containing alcoholic drinks made from fruit, rice and honey that produced as early as 7000 BC in the Neolithic village of Jiahu (McGovern et al. 2004), and evidence of winemaking in Iran and Egypt at 6000 BC and 3000 BC (Cavalieri et al. 2003). With the innovation of productivity tools, the brewing technology was gradually perfected, forming a complete of production process including material pre-processing, fermentation and maturation. The long history has seen the development of a wide variety of TFABs, including beer, wine, Kombucha and cider. Because of the distinctive flavors and high nutrition contents, TFABs have become an important part of people's daily diet since ancient time. However, with the increase in food varieties and quantities, this traditional food is no longer seen as a first choice for most consumers. Food enterprises and research institutions are looking for transformative innovation in TFABs to make healthy, nutritious offerings that give a competitive advantage in the current beverage market.

In recent decades, consumers' preference for healthier food has become the primary consumption driving forces in the beverage market. The health-promoting attributes of TFABs have already been recognized through previous studies (Marsh et al. 2014). Roy et al. discovered that wine consumption increases the α-diversity of gut microbiota, which is believed to be beneficial to human health (Le Roy et al. 2020). Evidence also showed the antimicrobial and antioxidant properties of Kombucha (Costa et al. 2021; Kapp and Sumner 2019). As the as the dangers of alcohol abuse have been widely recognized, non- or low-alcoholic beverages more match consumers' health demands comparing to distilled liquor which is high in alcohol content, and TFABs seem to be the best choice that balance health and alcohol for both wine lover and health pursuer. COVID-19 pandemics have also created an opportunity

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for TFABs (Antunes et al. 2020; Nguyen et al. 2020). New research has found that moderate wine drinking played protective effects against COVID-19, possibly the effect of polyphenols, while consumption of beer, cider and liquor increased the COVID-19 risk (Dai et al. 2022). The powerful health benefits ensure long-term growth potential of TFABs in future beverage market.

A considerable effort has been made to improve the quality of TFABs in recent decades. However, traditional research methods on TFABs are inefficient, time-consuming and incomprehensive (Jian et al. 2021). Fermented alcoholic beverages are complex solutions consist of thousands of different compounds. The sources of these compounds include raw material (mainly cereals and fruits), microbial metabolisms, environment and post fermentation process (chemical and physical reactions during aging). Any changes in the fermentation process may lead to entirely different products, which means numerous attempts and evaluations are needed to finally develop desirable products through traditional methods. The emergence of metagenomics and metabolomics provides more comprehensive microbial and metabolic profiles of traditional fermentation systems (Gao, Hou, et al. 2021; Mannaa et al. 2021; Tamang et al. 2016). Though most of current research on TFABs is stilled limited in small datasets, the exponential increase in the amount of relevant data combined with newly-developed data mining methods will provide a new way to understand and improve the fermentation process comprehensively.

Artificial Intelligence (AI) is the study of applying computer or computer-controlled robots to perform tasks by simulating thinking processes and intelligent behaviors of human beings. Machine learning (ML) is a key problem for AI, of which research has a profound influence on data mining (Blikstein and Worsley 2016), machine translation (Brynjolfsson, Hui, and Liu 2019), natural language processing (Kantor 2001), voice and image recognition (Bishop 2006; Gonzalez Viejo et al. 2016). Computational modelling based on AI is a promising method to manage the data explosion of TFABs (Jian et al. 2021; Figure 1). Existing statistical methods are usually applied to small datasets, which is not enough to reflect complex fermentation system and satisfy the ever-increasing demand of consumers (Chen et al. 2018). The implementation of intelligent platforms enables companies and researchers to gather, store and analyze large datasets in a more convenient way. Numerous studies have shown high efficiency and accuracy of AI-based methods in food industries with big data. AI has been gradually changing the production and marketing process of TFABs.

In this review, we focus on the research progress of AI-based methods in TFABs development. Application of AI-based methods on TFABs has been a hot research topic both in academy and industry, involving different kinds of TFABs like beer, wine and sake. Though a series of research papers have done, as far as we know, there is no systematic review on application of AI approach on TFABs. We further combined the characteristics of TFABs with the machine learning, artificial neural network, Internet of Things, synthetic biology and big data and introduced the application of AI approaches in specific steps of supply chain of TFABs. Finally, we give a future prospect of the development and potential of AI approaches in practical application.

Industrialization of TFABs in big data era

Characteristics of traditional fermentation process

It is generally acknowledged that fermented foods originated from the imitation of natural fermentation. For the

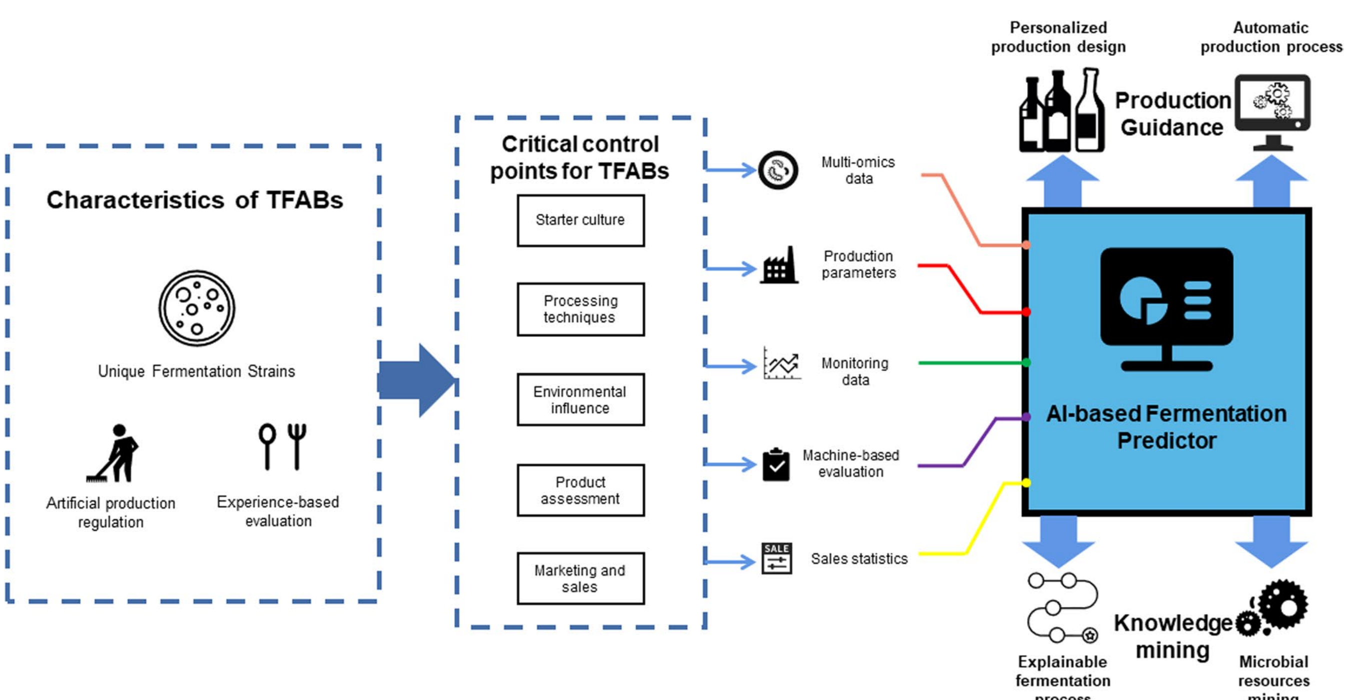

Figure 1. Data-driven methods change development of TFABs.

advantage of prolonging the storage time of grains and fruits, a considerable effort was made on technical and flavor improvement of traditional alcoholic fermented beverages for thousands of years (Figure 2). At the beginning, due to the lack of effective detection and analysis means, the brewing techniques were established through long-term direct observation and experience accumulation by humans. Then the development of microbiology and biochemistry revealed the nature of fermentation, thus further improving the production process. In recent decades, with the aid of bioinformatics and other high-throughput detection methods, the great potential was gradually realized by researchers and consumers.

Due to the increasing quantity demand for TFABs, traditional small-scale, household production systems are gradually replaced with modernized, industrialized production chain (Chen et al. 2018; Galimberti et al. 2021; Katz 2003). Mechanized production can be considered a simplified vision of the traditional fermentation process (Figure 3), which has a larger production scale and faster fermentation speed but produces lower contents of flavor and functional compounds. Three characteristics of traditional fermentation resulted to the quality differences in final products (take Huangjiu as an example) (Gui-Mei et al. 2021; Yang et al. 2020). A thorough understanding of traditional fermentation helps to improve mechanized production techniques.

Production techniques

The production and aging processes for TFABs are quite complex. The traditional fermentation process for Huangjiu follows a one-year-cyclic pattern: producing wheat Qu in the eighth month of lunar calendar, fermenting from winter and frying wine in next year's spring. Mechanized production can be conducted in any time with a 30-day production cycle. Besides, the scale for traditional fermentation is about 100 kilograms (raw material), while the scale for mechanized production is tens of tons (Xie et al. 2020). The difference in production cycle and scale lead to the complex layered structure of manual Huangjiu.

Mixed fermentation

Most traditional production processes are mixed fermentation systems. Microorganisms from starter culture, raw material and environment together dominate the fermentation process. The microbial interaction in the fermentation process forms a complex enzyme system, which promotes the formation of flavor compounds and nutrient components (Ren, Du, and Xu 2017; Jin, Zhu, and Xu 2017; Xie et al. 2021). Because of the stricter controls of fermentation conditions, there is less microbial resources for mechanized production, indicating low microbial diversity. Besides, the way of Qu-making also affects the formation of volatile flavor compounds. Compared with the Huangjiu brewed from mechanized wheat Qu, the Huangjiu brewed from handmade wheat Qu has stronger aroma and better taste (Peng et al. 2022). The importance of fermented microorganisms drives research on microbial structure (Hong et al. 2016; Cong, Hai, and Yan 2017), succession regulation and microbial interaction.

Experience-based sensory evaluation

Regularly monitoring of fermentation indexed is necessary to ensure the fermentation process to be carried out stably. Traditional production regulation mainly relies on human sensory perception to judge quality characteristics. Though the human assessors may be experienced wine tasters, the evaluation results can differ due to environmental factors

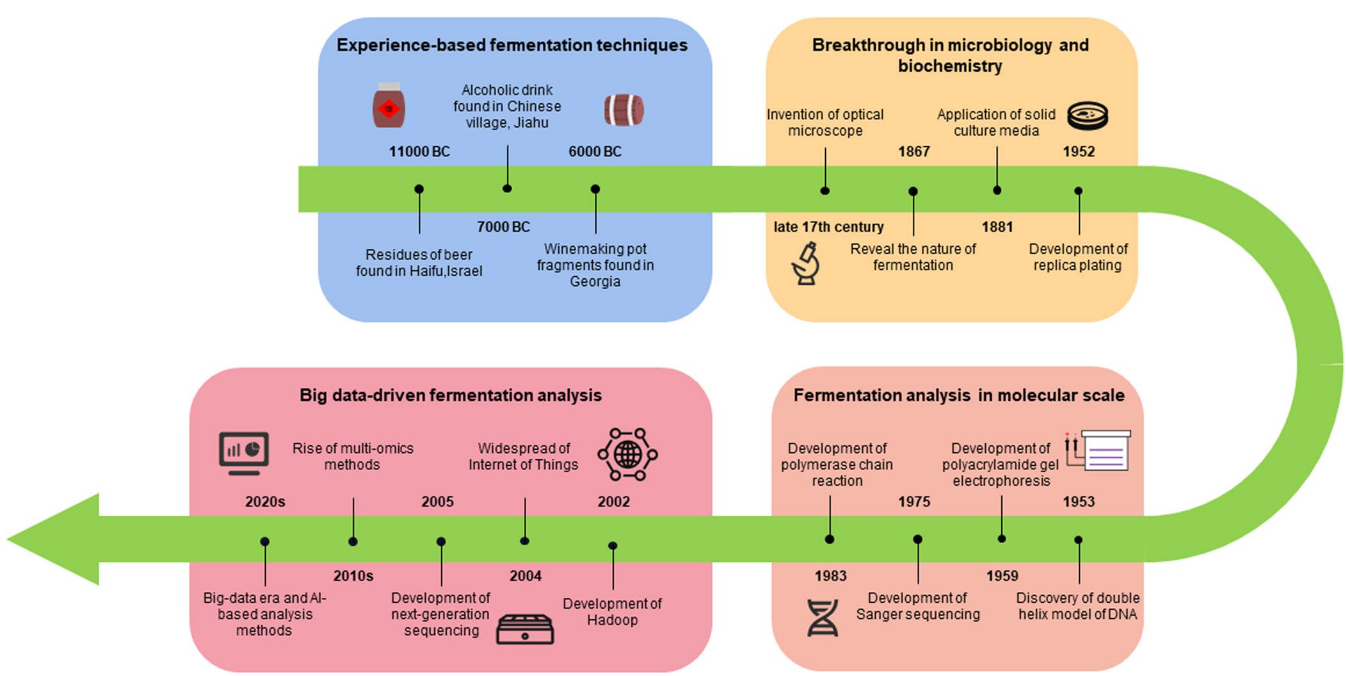

Figure 2. Development of TFABs.

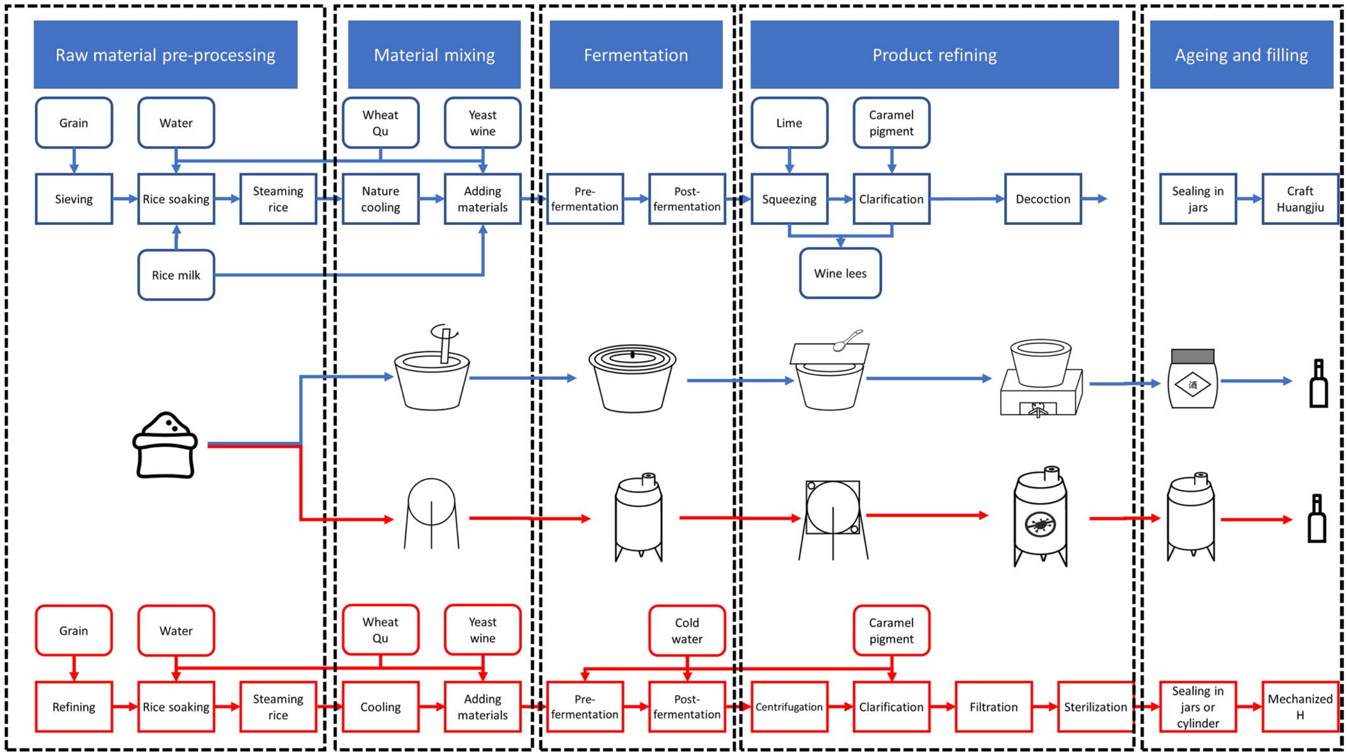

Figure 3. Production techniques for craft Huangjiu and mechanized Huangjiu.

and psychological variability. It's also time-consuming and strenuous to undertake enough manual assessment. Sensors in mechanized production line provide several fermentation indexes to help regulate production. However, existing monitoring methods are not suitable for large-scale production. For most TFABs, especially high-end spirits, experience-based sensory evaluation is still the dominant evaluation method. Though a great deal of work has done on combining sensory evaluation with other fermentation indexes (Nicolotti, Mall, and Schieberle 2019; Dresel, Dunkel, and Hofmann 2015; Yu et al. 2022), there is a lack of scientific data-driven method to evaluate the sensory properties of TFABs.

Challenges for development of TFABs in big data era

Big data emerged with three papers from Google, Google File System (GFS)(Ghemawat, Gobioff, and Leung 2003), MapReduce (Dean and Ghemawat 2008), and BigTable (Chang et al. 2008). Then the open source of Hadoop drove the boom of big data industry. From then on, data technology was used in a wide range of fields, including TFABs. Digitalization, or digital transformation, refers to the process of converting information into a digital form and adopt digital technology to help make decisions. With the development of Internet and digital economy, digitization has become a general trend for TFAB industry to avoid others' digital disruption. Last decade saw exciting changes in both amounts of data and the application of that data in TFAB industries. The continued evolution of data technology has led to impactful new technology and popular new products of TFABs. For the advantage of intelligent decision-making, it's the top priority to transform into a data-driven business for most TFAB enterprise. Due to the limitations of traditional industries, many of the TFAB enterprises are struggling with the digital transformation. The rapid advancement in digital transformation has brought with a range of challenges that will define the future trend of TFAB industry.

The challenges raised by big data are summed up as 4Vs: volume, variety, veracity, and velocity (Lee and Yoon 2017). The development of multi-omics methods (Mannaa et al. 2021; Rizo et al. 2020; Prakash et al. 2013), sensor technology (Tan et al. 2022), and human interface devices (Tonkin, Brimblecombe, and Wycherley 2017) lead to more available data of TFABs. However, too much data can be overwhelming, as only part of it works for specific decision-making. Though valuable information can be found in properly processed data, it's not easily to manage raw data. For companies that have extensive data already collected, it is time-consuming for implementation team to rearrange the current data and make difficult choices. The rapid development of data acquisition methods also poses the problem of data management. The data to analyze comes from various sources in different formats. Meanwhile, large datasets are prone to error and miss, challenging for big data analytics. The enormous complexity of data not only makes it hard for computers to understand data in different formats, but also increases the difficulties in establishment of databases. Raw data does not help to develop a new product or optimize existing techniques, which is a competitive requirement for leading enterprises to cope with. It's of great importance to construct a reliable data mining framework to take full use of these data in further study (Dayioglu and Turker 2021; Hassoun et al. 2022).

Applications of AI-based methods in TFABs

Data mining is the process that extracts implicit and potentially useful information from data (Mahmud et al. 2021; Salehan and Kim 2016). Big data and data mining are reshaping all areas of modern industry. Establishing a model from data through different algorithms is an important step in data mining process. AI-based methods are the typically used algorithm to create solutions in mined data. Comparing to traditional statistical methods, AI-based methods perform more productive and precise in undertaking big data tasks. Thanks to the application of open-source programming language and relevant packages, such as Python (scikit-learn) and R (knn, naiveBayes, C5.0, etc.), it's also convenient to start a machine learning project from data acquisition, data pre-processing to modeling.

AI-based approaches are also revolutionizing the food industries and helping solve complex problems. Though still in the early stage, many attempts have already been made with big data created by intelligent devices and sensors. Some food manufacturers of TFABs have cooperated with tech companies to uncover useful information from the production data and further improve the production process for the development of popular products. It is the basic and most important function for AI applications to simulate human learning behavior and make decisions. A large number of reviews have already proposed the possibility of applying ML methods in the development of TFABs (Chen et al. 2021). A typical modeling process (Figure 4) for ML could be broken in 5 steps: data acquisition, data pre-processing, data modeling, model evaluation and model deployment. Problem complexity, data quality and model selection play a crucial role in the final model performance. Up to now, the predictive power has been applied in TFABs in some way, mainly using prediction models with production data and consumer data to assist decision making.

The aim of AI-driven supply chain of TFABs is to link data assessment to the production and marketing process, and to help make decisions in a way that humans can understand. The big data of TFABs are analyzed through AI-based methods to improve critical control points, including fermentation process, environmental control, mixed bacteria system regulation, sensory evaluation, and so on. New AI-driven approach for TFABs (Figure 5) is expected to give rise to further in-depth exploration both in the academy and industry.

Process optimization

As previously mentioned, experience-based evaluation is a committed step for the flavor control and process optimization of traditional fermented food. Experienced staff regulated and controlled the production process by observing the changes in fermentation. However, decision fatigue and error are inevitable in human decision-making, which is a significant cause for the differences between batches. Computer vision is an important search field of AI that enables computers and robots to percept, recognize and interpret the real world through digital image or video. The application of computer vision systems to control the manufacturing process has become increasingly popular in the food industry in recent years. Japanese sake brewery Nanbu Bijin has developed an AI tool to monitor the water absorption find the best time to drain water before steaming the rice through a huge number of production images. Asahi Shuzu and Fujitsu also launched trial of combining a mathematical model defining the process of sake brewing with machine learning that uses data obtained in the brewing of DASSAI. The final predictive AI model is expected to provide data to support an optimized sake brewing process. The application of AI-based approaches promotes progress in production techniques of TFABs. However, these applications are mainly regulated for a specific step in the fermentation process. A comprehensive monitoring and regulation system are necessary to brew better TFABs.

It's an important issue to improve the traditional brewing process to adapt large-scale industrialized production. With the dramatic drop in the costs data storage, it is cost-effective for food manufacturers to collect and store large-scale production image data. The application of computer vision techniques not only facilitates the industrialization and

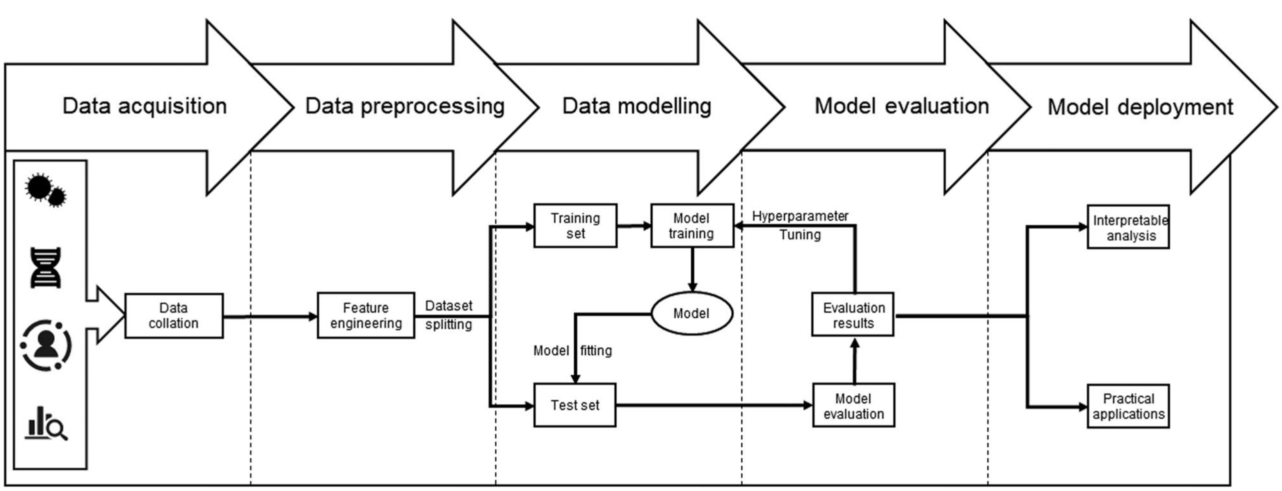

Figure 4. Typical ML modelling procedures.

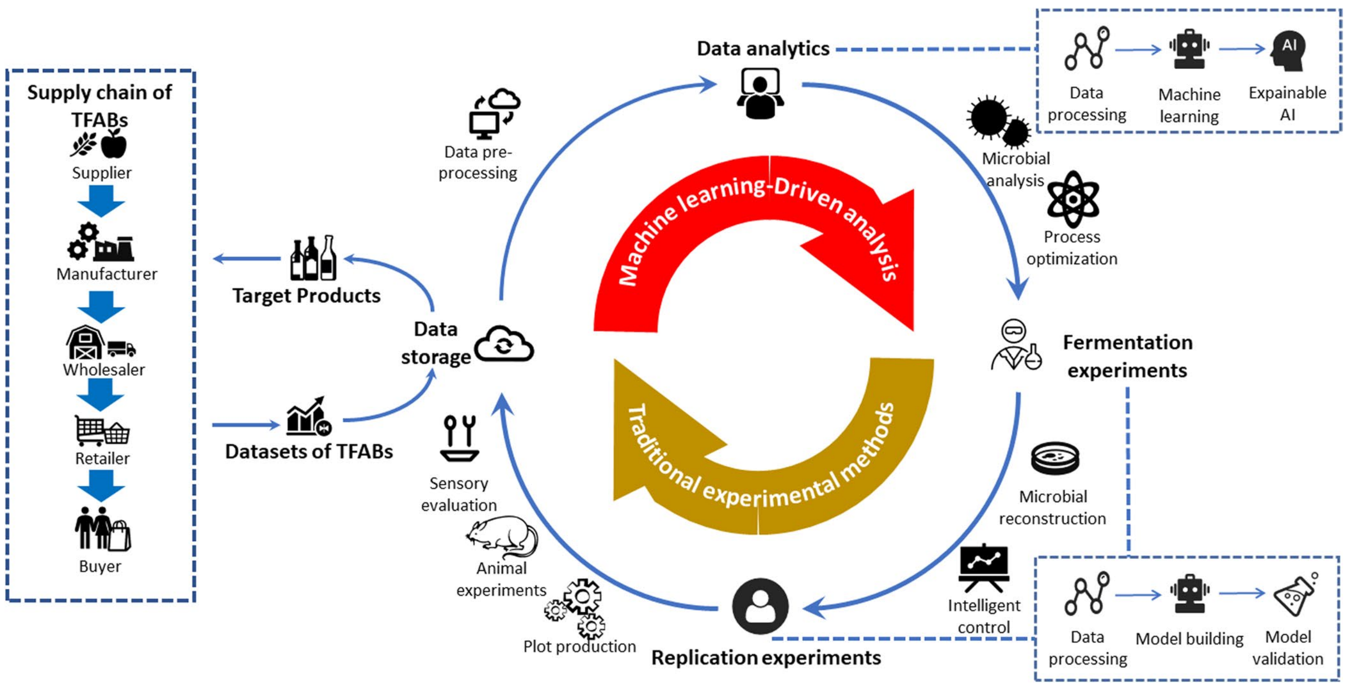

Figure 5. ML-driven approach for research of TFABs.

automation process of TFAB industries, but also improves the productivity and accuracy.

Product grading

Sensory evaluation refers to a scientific discipline that measures the human reactions to the characteristics of food as they are received by their sense (Lesschaeve 2007; Cejka and Olsovska 2015). Sensory properties are considered one of the most important factors that determine food quality, especially in TFABs that have a complex flavor composition. As mentioned above, while the results of manual sensory evaluation are easily to be affected by environment and emotion, data-driven sensory evaluation system is necessary to ensure product stability. One of the examples of AI application is identifying liquor age. Many of the TFABs are highly-valued products and maturation has a marked influence on sensory qualities, as well as market values. Because of the wide application of blending techniques, it's difficult to discriminate the quality or age of TFAB. Identification of age-markers is challenging because the complexity of flavor substances and exogenous compounds generated from the production process. Alibaba introduced ML method in adulterated wine discrimination and developed Jianzhen AI Maotai-discrimination box. From the data of image recognition, weighing, optical scanning and other methods, the AI box identify the basic information and discriminate authenticity and vintage. Gonzalez Viejo et al. (2016) developed a robust robotic beer pourer, RoboBEER, which analyze foamability, bubble size, alcohol content, temperature, carbon dioxide release and beer color to assess beer quality. The Artificial Neural Network technique used in RoboBEER for pattern recognition creates a classification model that achieves 92.4% accuracy in the classification according to quality and fermentation types. Besides physicochemical indexes, AI approaches can also take good use of other data to further visualize the sensory properties to consumers, not just a black-box classification model.

Customization marketing and production

With every day developing online shopping, intelligent recommendation system has become an important part for e-commerce (Gao, Liang, et al. 2021; Senecal, Kalczynski, and Nantel 2005; Zeng et al. 2019). As most people can only experience limited amount of TFABs, and they don't have enough professional knowledge to judge quality of TFABs, personalized recommendation model has wide application prospect. AI algorithms are applied to analyze the interactions with purchasers and provide proper products that will interest consumers. AI-based consumer analysis models are efficient dealing with unstructured interaction data and are helpful to discover the key deciding factors for most potential customers. AI models can make customer behavior predictions and integrate buyer personas to recommend suitable products. With the fast-growing quantity of interaction data, AI-based recommendation system is crucial for TFABs and other companies to search and filter useful information to the customers. The app Wine Ring offers one of the best personal wine selection experiences. It is the first to use AI-driven approaches to make wine recommendations based on individual preferences. The more wine you drink and rate, the more suitable wine AI could recommend. Another app for wine recommendation is Vivino, the world's largest online wine marketplace (Mastroberardino et al. 2019). Up to 2021, Vivino has a wine database of more than 12.5 million different wines, providing services for 50 million users. AI approaches help to push the boundaries of the traditional fermented food industry in the future.

The understanding of individual preferences through AI further enables TFAB manufacturers to realize personalized customization (Busse and Siebert 2018; Tonkin, Brimblecombe, and Wycherley 2017; Senecal, Kalczynski, and Nantel 2005). The widespread use of smart devices makes more information of personal preferences available to enterprises. Extensive researches on demand mining and the traditional fermented food industry have been taken to understand and meet consumers' needs. British IntelligentX has put forward the world's first beer that used AI algorithms and ML methods to help adjust the recipes. IntelligentX created four different kinds of beer: Black AI, Golden AI, Pale AI, and Amber AI. By answering 10 questions associated with the products, IntelligentX collected feedback through Facebook and then improve the recipe. Charlottesville's Champion Brewing company cooperated with a machine learning company Metis Machine to brew their new ML India Paleale (IPA). They provided parameters on the evaluation of 10 best-selling IPAs in the Great American Beer Festival, as well as 10 worst-selling IPAs, to create a popular IPA recipe. With existing recipes and interaction data collected from smart devices, AI-based methods show great ability to design popular recipes for TFABs. Though master wine tasters are still necessary to evaluate the product quality and decide the final recipe from AI-designed recipes, AI-based methods are proven to be a promising way to simplify the processes of new product development and personalize customized products.

Future prospect of potentials of AI-based methods in TFABs

Though AI-based methods have been applied in TFABs to some extent, there is a large potential for further development on both theory and application. Current AI-based application and research focus on the datasets of production and consumer data. Multi-omics datasets allow a better understanding of complex microbial system and so becomes primary methods for research of TFABs (Bokulich et al. 2016; Mallick et al. 2017). The combination of AI-based methods and multi-omics datasets is an effective way to optimize the fermentation process. In addition, applied studies are carried out more than theoretical studies. Actually, AI is an effective data mining method to reveal unknown phenomena and essence in the traditional fermentation process. Explainable Artificial Intelligence (Samek, Wiegand, and Müller 2017; Linardatos, Papastefanopoulos, and Kotsiantis 2020; Samek, Wiegand, and Muller 2017) is a set of math techniques that help humans to fully understand the decision-making process of the model in safety-sensitive tasks, such as medicine and food. It provides a whole new perspective to explain the decision-making process and guarantee the security of AI-based methods used in TFABs. More importantly, applications mentioned above in TFABs are similar to those in other manufacturing industry. Rational use of AI-based methods according to the characteristics of TFABs helps to maximize the advantages of these long-lasting traditional foods.

Production regulation

Open fermentation or semi-open fermentation is a major characteristic of traditional fermentation (Zhou et al. 2021; Wang et al. 2022). Though part of keeping things sanitation is keeping the fermentation materials closed to the production environment, some brewers insist on open fermentation. It's believed that open fermentation promotes the formation of flavor substance. For these reasons, environmental control is necessary for ensure product quality. In general, several parameters have to be adjusted in the fermentation process, including temperature, time and humidity. However, the influence of environmental changes to TFABs cannot easily be quantified. A number of research have been done to explain the traditional fermentation process and bridge the flavor gap between craft products and mechanized products (Sanna and Pretti 2015), and powerful tools are developed to describe the traditional fermentation process in a scientific way to help regulate the fermentation process, including predictive microbiology (Lopatkin and Collins 2020). It's possible to apply AI-based methods to learn from the traditional fermentation process and regulate the industrialized fermentation process.

The growth in the number of connected devices that make up the Internet of Things (IoT) suggest that the environmental data is more than ever before, making it possible to monitor and regulate the whole fermentation process (Ben-Daya, Hassini, and Bahroun 2019; Hansen and Bogh 2021; Lu 2019; Zhang and Tao 2021). Instead of using IoT separately, AI algorithms can be integrated within connected devices to enable intelligent decision-making. IoT complements well with AI, and most IoT platforms (Azure, IBM, Splunk, AWS, and Google) make good use of AI for aided decision-making. AIoT, or AI + IOT, is the combination of AI and Internet of Things in practical application (Idoje, Dagiuklas, and Iqbal 2021; Zhang et al. 2022). IoT devices generate huge amounts of data that AI approaches can take advantage of to analyze and track. Combining AI with IoT in this way can create "smart devices" that can make informed decisions without human intervention to realize the regulation of microbial communities. Integrating big data with predictive microbiology to build dynamic models of fermentation (Figure 6) will also yield meaningful returns. With smart food production line and environmental monitoring system, AIoT is expected to bring benefits to TFAB industry in terms of efficiency and safety through environment regulation (Jagtap et al. 2020).

Construction of starter culture

Due to the great contribution of microorganisms on fermentation process, microbial analysis has been a research focus in TFABs (Zhang et al. 2019; Zhou et al. 2021). Driven by high-throughput sequencing techniques (Mardis 2008; Clarke et al. 2009), genomics data grow exponentially in

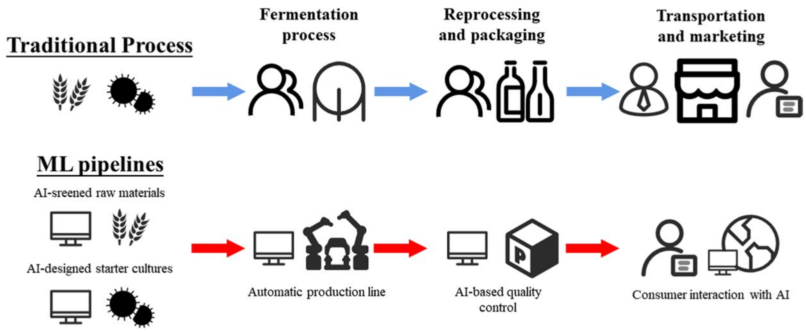

Figure 6. Traditional fermentation process and AIOT-driven automated production process.

volume, variety and complexity. The emergence of AI techniques provides a new idea for data mining of high-throughput omics data in big data era. Quantitative Insights Into Microbial Ecology (QIIME) (Caporaso et al. 2010), a tool to explain the data generated by sequencing, was put into use in 2010, which marked the application of ML methods for microbiome analysis. Thanks to high-throughput sequencing techniques and ML methods, recent studies have revealed microbial diversity and structure in the traditional fermentation process. AI-based data mining tools transfer vast amount of omics data to comprehensible knowledge, which performs well in microbial analysis (Lim et al. 2022; McElhinney et al. 2022; Gao, Zeng, et al. 2021). Though ML methods have helped to analyze microbial structure in the fermentation process and promoted the research of traditional fermented microbiome to some extent, the study of fermentation mechanism is insufficient. The analysis of microbial interaction and fermentation driving force has always been the key and difficult points of traditional fermented food research. Current statistics methods are difficult to realize real-time regulation of fermented microbiome. Explainable Artificial Intelligence helps to transfer multi-omics data to understandable knowledge. It is promising to apply ML methods to the analysis of multi-omics data generated during fermentation and to use Explainable Artificial Intelligence to analyze microbial interactions and fermentation driving forces.

An important goal of microbial analysis in TFABs is to construct efficient starter culture (Wei et al. 2021). Traditional research methods optimize production techniques of starter culture or reconstruct fermented microbial community referring to functional analysis. Fermentation experiments that simulate real production environment are then conducted to evaluate fermentation performance. This microbial community construction method is usually local optimization, aiming at increasing or decreasing contents of specific metabolite (Du et al. 2021). Further research is needed to construct efficient fermented microbial community and reveal the relation with metabolic profile through multi-objective optimization.

The ML-based analysis combined with metabolomics and metagenomics has already been done in the field of medicine (Bar et al. 2020), indicating the potential of AI to explain the microbial metabolism and to reconstruct microbial community in TFABs. Comparing to gut microbiomes, the fermented microbial structure and metabolic composition is relatively simple. Thus, the modeling and analysis of gut microbiomes can be applied in a similar way to the study of fermentation microbial community and enables us to get better prediction and validation results. The driving forces of the fermentation system can be visualized based on the ML model with metagenomics and metabolomics. Then the core fermentation microbial community is established according to feature attribute analysis brought by Explainable Artificial Intelligence. Data mining of core microbial community is carried out with metabolome to explain the mechanisms of traditional fermentation. These ML approaches shed light on the metabolic mechanisms of the core microbiome and help to develop efficient starter culture.

Sensomics and flavor network

The composition of flavor compounds is not equal to flavor characteristics (Jian et al. 2021). Though flavor characteristics have a notable influence on purchase tendency, the complex kinds and compositions of flavor compounds make it difficult to quantify flavor contribution. Traditional manual sensory evaluation is subjective and difficultly recurred by assessors. However, it's not easy to establish an objective data-driven evaluation method. Traditional statistical methods unable to process complex flavor information in time and realize global optimization.

Sensomics is considered to be the leading-edge science that molecularizes flavor entities (Vrzal and Olsovska 2019), thus has been applied to knowledge-based flavor optimization and authentic flavor reconstruction in TFABs (Nicolotti, Mall, and Schieberle 2019; Sun et al. 2022). There are application prospects to combine sensomics with big data and AI technology to construct flavor network, explain flavor contribution, optimize flavor of existing products, predict popular flavor entities and develop novel products of TFABs.

Discussion

AI-based approaches provide an opportunity to optimize and automate the production and marketing processes of TFABs. In this review, a systematic effort has been made to detect the benefits and potentials of applying ML methods on research of TFABs. The study also proposes a framework for intelligent control fermentation system. It is observed that ML methods have been applied on production and marketing for decision support. Though these attempts are innovative in TFABs, similar applications can be found in other fields. Three potential applications that correspond to the characteristics of traditional fermentation process are suggested to develop distinctive products of TFABs. The vast volume of data created by multi-omics and IoT will be fully taken advantage of in these applications. Intelligent control of the fermentation process is one of the main goals for industrialization of TFABs, and at the same time the multi-omics analysis of metabolic mechanism and microbial interaction is one of the greatest challenges in the research of TFABs. This study has suggested AI approaches as solutions to these issues. It is expected to give rise to further in-depth exploration toward a directed regulation strategy of the fermentation process through the employment of ML methods.

AI-based techniques are promising to be the most transformative data mining method for TFABs production chain due to the great predict ability and high efficiency in big data era. Though the applications and potentials mentioned above are encouraging, the employment of ML techniques should also be cautious for several reasons. The ML models are highly efficient in prediction, but it always takes a lot of time to provide more accurate results. Besides, the traditional fermentation production techniques are proven to be effective according to thousand years of experience, while the prediction results of ML methods are based on data, lacking scientific support. The uneven data quality may lead to false prediction and cause food safety problem. Up to now, AI-based methods should be regarded as decision aids for humans. It requires long-term monitoring and experiments to validate the security of ML methods.

To sum up, AI approaches could push the process of industrialization and automation of TFABs chain and guarantee the quality. Nevertheless, challenges exist in data quality, model explanation and shortage of AI talents. Despite the limitations, AI techniques should be regarded as an important tool for the development of traditional microbial resources and targeted regulation of traditional fermentation process in the future.

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