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# Impact of AI on the Brewing Industry: A Comprehensive Summary

**AI has been gaining incredible momentum in the public perception throughout the past year. The main trigger has been the media effective presentation of ChatGPT, presumably. Suddenly, a use case for AI graspable for each and everyone had been created, making the topic directly available to the public mind. Plenty of diverse discussions are ongoing since, be it fantasizing on future use cases, experimenting with the technology (sometimes seemingly "throwing" AI on pretty much everything, treating AI as the "Holy Grail" of technological progress), critical voices full of emotions (especially various subjects towards anxiety) or profound neutral analysis of potential use cases from a scientific point of view. However, both enthusiastic and critical discussions very often lack fundamental background knowledge of the technology behind AI along with what potentially is realistic to implement. Generally, a comprehensive discussion of AI needs to be carried out on various levels, including a more socio-economic overview of the impact of AI on the public, a summary of the technology behind AI to a depth naturally limited by the nature of an article like this, and finally a review of current real use cases. The purpose of this article is to discuss the aforementioned fields in the context of the brewing industry. The main focus will be on a basic introduction of the technology behind current AI trends in the relevant field along with non-classic sensors used to implement new use cases and applications. This summary is followed by a presentation and critical discussion of already existing industrial use cases. It will be shown: AI has already arrived in the brewing industry – longer than the publicly perceived existence of ChatGPT.**

Descriptors: brewing-AI, electronic nose, electronic tongue, smart sensors, AI, deep learning, AI driven business models, AI for quality enhancement

## 1 Introduction

Artificial Intelligence (AI) is one of the dominating technologies currently, overcoming frontiers between different scientific disciplines, economical branches and geographical borders [1]. The momentum being present in the public mind gained significantly along with the media effective presentation of ChatGPT, despite the latter being just a tiny, while widely tangible, application of the AI technology [2–9]. Since then, diverse and controversial discussions can be observed, being filled with enthusiasm and anxiety, optimism and skepticism, hope and doubts. As well, as mentioned before, different topical fields are affected by the technology, which cannot even be clearly treated independently [1]. The complex core of this topic has been discussed in [3] in the context of generative AI like ChatGPT, provided by an international crowd of experts covering various fields influenced. The opening statement is given as

[...] we provide a state-of-the-art interdisciplinary overview of the probable impacts of generative AI on four critical domains: work, education, health, and information. Our goal is to warn about how generative AI could worsen existing inequalities while illuminating directions for using AI to resolve pervasive social problems. Generative AI in the workplace can boost productivity and create new jobs, but the benefits will likely be distributed unevenly. In education, it offers personalized learning but may widen the digital divide. In healthcare, it improves diagnostics and accessibility but could deepen pre-existing inequalities. For information, it democratizes content creation and access but also dramatically expands the production and proliferation of misinformation [3].

Obviously, AI and its surrounding technology along with real use cases is a polarizing topic. As stated by Stephen Hawking on BBC [10]:

*The rise of powerful AI will be either the best, or the worst thing, ever to happen to humanity. We do not yet know which.*

Anxiety and skepticism are well known patterns when it comes to the arrival of new technologies, significantly while not exclusively nourished by deficits of information. E.g., AI is frequently perceived as a tool for creating something disruptive, new, never-seen, ... Though, AI may also be used to recreate something vintage and continue traditions. One example for this is a German TV series for kids, which is currently being reanimated by using AI to reproduce the voice of a 20 year long dead actor being linked to a central character [11]. This use case does not harm anybody, but pleasures nostalgic fans only. As can be seen, there is for sure more than only one facet on AI, if used appropriately. The purpose of this article, therefore, is to describe the technology behind AI from a top-level view to open the arena of discussing the AI topic in the brewing context in front of a more informed brewing crowd on a much broader level than currently possible. For sure, experts in the field of AI ap-

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plied to brewing per se already possess excellent skills to use the technology for their advantage – how, else wise, would it be possible, that AI already has great impact on the brewing industry?! Still, the industrial branch of brewing in general is comparably conservative, bringing the need forth for an educational discussion on AI to the average player in that area.

In fact, there are already plenty of fields of application for AI in the brewing industry, overviews being given, e.g., in [2, 12, 13]. Fields covered include, e.g., the development of new business models and product development processes [14, 15], education and training [16], consulting [17], supporting technologies for craft and hobby brewers [18–23], generation [24–32] and analyses/adjustments of beer recipes [33–39], design aspects [24, 28, 32, 40], marketing [24, 41–43], potentially including customer feedback [28, 37, 44–47], digital beer sommeliers [48, 49] and review creation [50], beer quality analysis related to haptic aspects [51–56], flavour perceptions [15, 57–63], fermentation process observation and optimization [18, 22, 64–67], automated beer fault analysis [68], raw material quality checks [69, 70], automated brewing process optimization [71–73] including automated lab based issues [74, 75] or even including biometrics and cognitive perception for beer acceptance prediction [76–78]. Meanwhile, even competitions between human and machine brewers or finally between different AI brewing instances are being carried out [79].

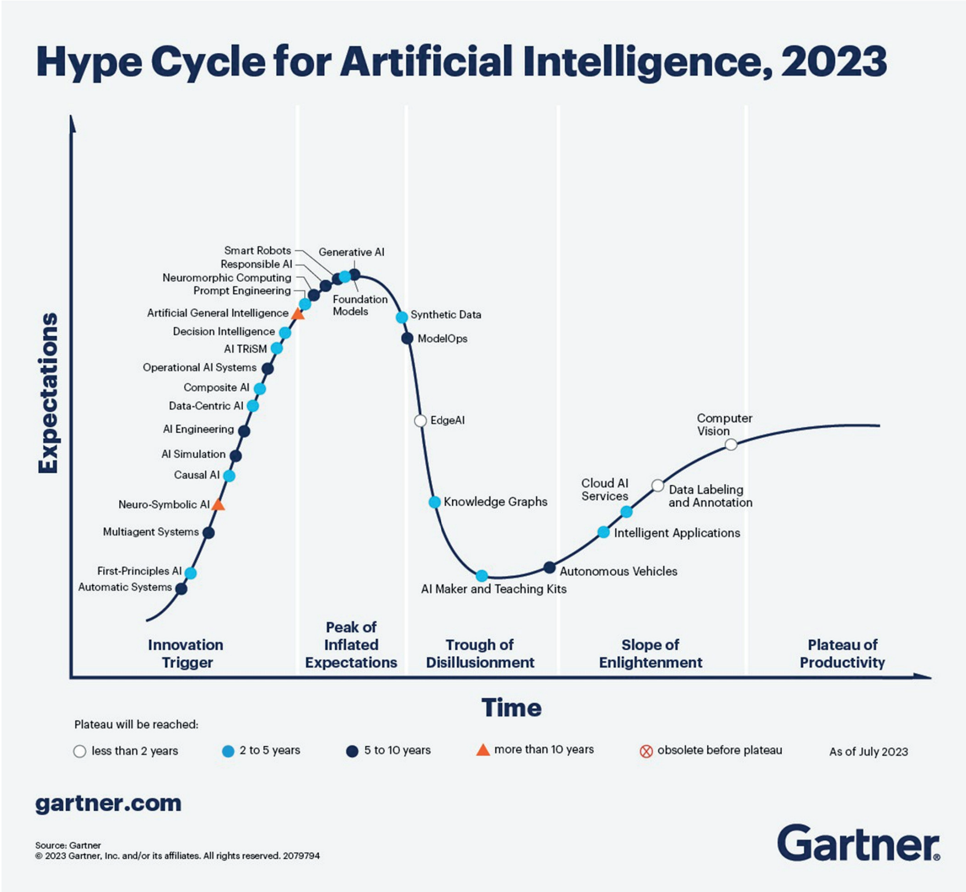



**Fig. 1** **Gardner Hype Cycle for AI in 2023 [86]**

This article is structured as follows. Section 2 dives deeper into the (technical) background of the AI technology used to implement the aforementioned use cases in the respective fields. Section 3 provides a description of auxiliary technologies in the beer technology sector, which are required to feed the AI algorithms being used to fulfill the use cases. Section 4 presents the individual listed use cases in more detail, while Section 5 critically discusses the previously developed findings in the context of future usage of the technology. Finally, Section 6 concludes and summarizes the article.

## 2 AI Technical Background

The history of AI has not started with the media effective presentation of ChatGPT this year or not even 5 years ago. Actually, following some sources like [80] the origin of AI may be dated to 1936, when *Alan Mathison Turing* presented his theory of the Turing Machine, being the proof, that computers are able to deal with cognitive processes [81]. A first major application based proof for this cognitive process awareness was the treatment of the mathematics behind the Enigma coding machine and the resulting proven capability of the Turing Machine to perform the decoding process [82, 83]. More commonly, other sources like [84] treat the year 1950 as the start of the AI development, when Turing published his paper about "Computing Machinery and Intelligence" [85]. This was a theoretical break through. Still, only since a couple of years computers are powerful enough to implement a significant portion of the theoretical potential in real systems.

Figure 1 illustrates the current maturity level of various fields of AI represented as the Gardner Hype Cycle curve for AI in 2023 [86].

The typical five cycles can be observed, defining the maturity status of each and every technology or application of technology. It can be seen, that some applications of AI (e.g., Cloud AI Services or Autonomous Vehicles) show already some great extend of maturity. On the other hand, applications like Generative AI (e.g., ChatGPT) or Responsible AI are currently seen in the phase of Inflated Expectations, reflecting a comparably low maturity level. Summarized: many applications are already on-the-go, while others stoke a multitude of high expectations, which might or might not come soon (… or later). A similar scenario can be drawn for the beer industry. Many solutions on AI are already in place and help to save production cost on low cost devices, such as RaspberryPi used to control the fermentation and/or brewing process [18–23, 65–67], while other applications may only be implemented in the near or far future. Essentially, AI seems to provide disruptive solutions – which might partially be true. However, overall and objectively speaking, AI is just another tool – and if a very power full one – for solving technical problems, especially when huge amounts of data are involved. To elaborate on this hypothesis a bit more, the following section

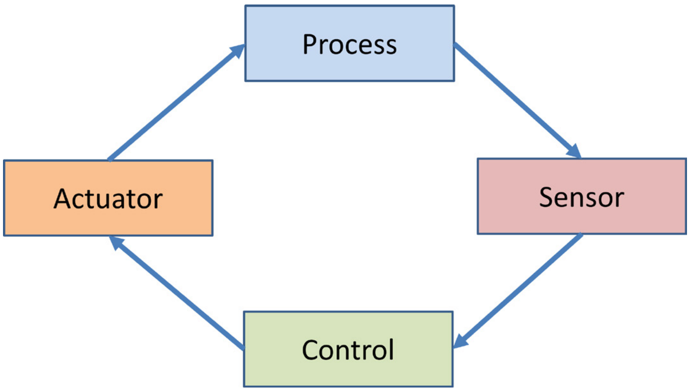



**Fig. 2** **System Level View of any Control System**

discusses a top-level and abstract view on simplified system architectures involving feedback and/or learning.

## 2.1 System Engineering Basics

Each and every field of our lives is following a basic principle: we perceive something (sensing), process the information and derive conclusions (control), execute the derived actions (actuator) – and with the latter influence the environment (process). Figure 2 illustrates this statement in a generic way.

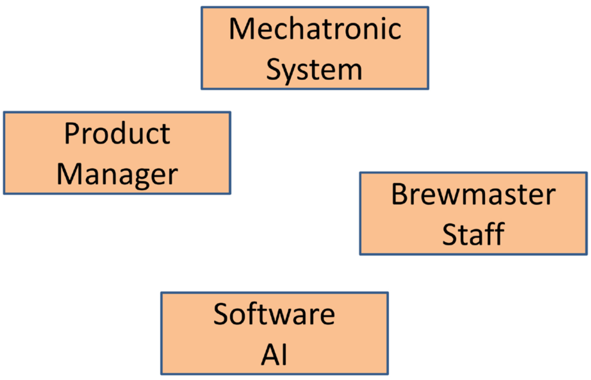
This is the starting point for defining a system architecture. In reality, the individual fields (sensor, actuator, control, process) are replaced by their concrete counter parts. In our context, the "process" may be the brewing process, which is observed by various sensors (e.g., temperature sensor). Based on the temperature, it is decided (control), that the heating (actuator) may be switched on or off. Figure 3 provides more options of "players" in the various fields, while this representation is by far not exhaustive, being given for illustrative purposes only.

What can we derive from this? In the more vintage approach, the process may be the brewing process, while the brew master is acting (executing manual valves), sensing (visual check), and controlling (derive actions from experience). The other extreme would be, that acting, sensing and controlling are all replaced by AI. AI could, e.g., extract information from huge data sources (sensing), derive conclusions (controlling) and adopt recipes based on the conclusions (acting) for improving the process. This is, e.g., used in reality in [72].

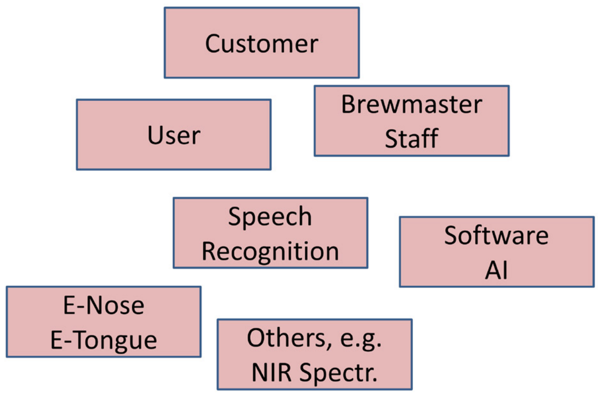
This example is given to trigger the reader's phantasy on what might be possible combinations of technologies used in the context. Depending on the purpose of the technological investigations, more or less portions of the system architecture may include AI as a support.

## 2.2 Procedure for Defining the System Architecture

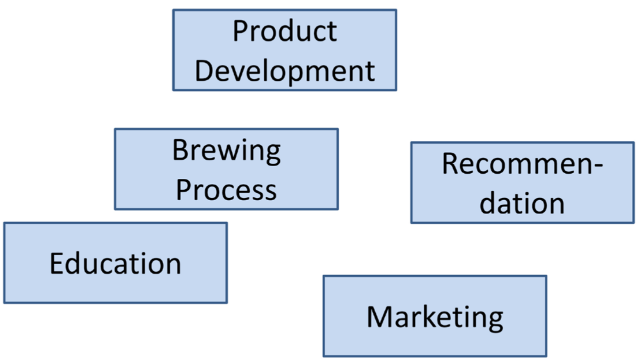
In this section, the individual steps towards defining a system architecture are defined. Obviously, a first step is to define the



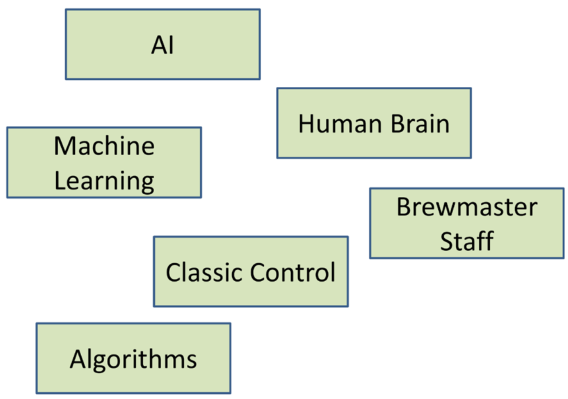

(a) Potential Representatives for Actuators




(b) Potential Representatives for Sensors

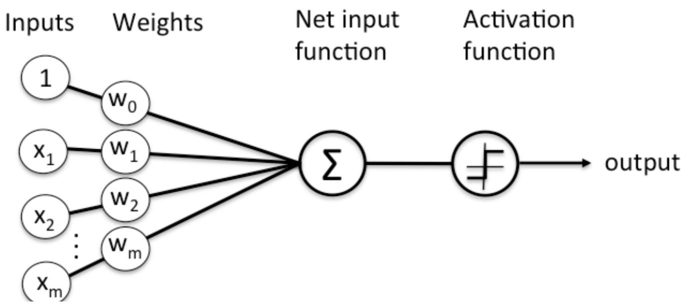



(c) Potential Representatives for Processes

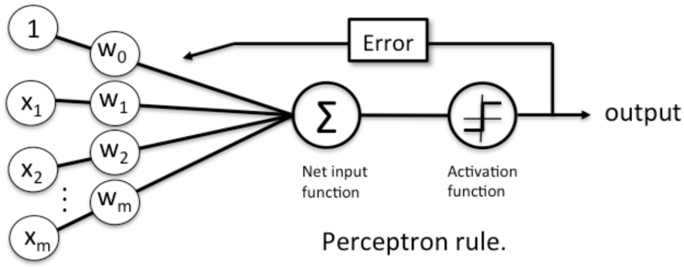



(d) Potential Representatives for Controls

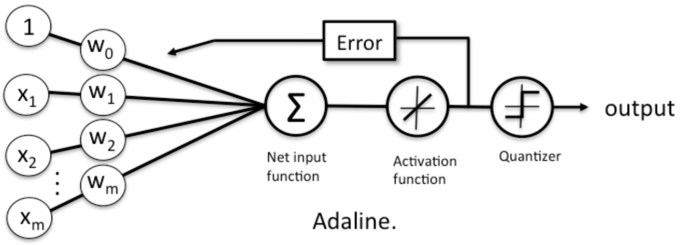
**Fig. 3** **Exemplary „Players" in the Different Control Loop Components**




(a) Rosenblatt Perceptron - with w1...wm = 1 we end up with McCulloch-Pitts [95, 96]




(b) Rosenblatt Perceptron with Feedback [96]




(c) Widrow Adaline with Feed- back [97]

**Fig. 4 Different Variants of Initial Neurons [98]**

"process" to be on the scope. Should the brewing process be optimized [71–73], the product development supported [28, 37, 44–47], digital marketing and product design enhanced [24, 28, 32, 40]? This needs to be fixed first.

Based on this, it needs to be derived, which "sensing" data is relevant. Is it customer opinions, e.g., based on social media feeds [46, 47], already compressed data evolving from data analysis or real sensor signals, e.g., from electronic noses (e-nose) or tongues (e-tongue) (will be discussed later) [57, 58, 87]? The right choice of "sensing" data is essential for a successful process influence.

The provided "sensing" data is then used to derive conclusions in the "control" part of the system architecture. The base for this conclusion may be established algorithms for control or AI algorithms. Whatever suited best is to be chosen. Non-classic algorithms may include Game Theory, Fuzzy Logic, Genetic Algorithms or Neural Networks (NN). In [88] a comparison of AI methods based on signals from e-nose sensors is given, including plenty of secondary literature describing the individual algorithms and data sources. Widely, in the context of AI, NNs are identified and linked towards solving AI problems. For this reason we will have a closer look in this aspect and implementation in the following section.

Finally, the made decisions based on "sensing" and "control" need to be executed ("acting") to influence the desired process.

This may involve automated or manual valves, recipe adoptions, heatings, cooling devices, social media feeds. As can be seen, the abstraction of the system architectural level allows to generalize the seemingly very technical approach, leading to a better understanding of the real implementation of applications, described in more detail in Section 4.

## 2.3 Artificial Intelligence and Neural Networks

Very often, AI and NNs are used interchangeably, while this assumption is not true. For sure, NNs play a major and central role in building AI systems, while NNs are not the only tool to implement AI. Other techniques or algorithms may include Decision Trees, Support Vector Machines [58], Hidden Markov Models, Bayesian Networks, Linear Regression, k-means or Tabular Reinforcement Learning (e.g. Tabular Q-learning) [89]. Decent literature on AI provides a more comprehensive insight into the whole palette of possibilities, e.g., in [90–94].

Still, as NNs play such a central role especially in the field of Generative AI (e.g., ChatGPT) and other Deep Learning approaches, in this paper only the basic concepts of NNs will be explained on a top-level view to establish a basic and broad understanding of this technique among the brewing community.

NNs are – as the name suggests – linked to the structure of the human brain and the neural network structure feeding the brain, distributed among the whole human body. This close functional link may be one reason, why especially NNs are linked to AI in the public perception so much. Each NN consists of a network of neurons. Figure 4 illustrates different types of neurons having developed over time.

The McCulloch-Pitts perceptron defined in 1943 [95] is a special case of the Rosenblatt perceptron shown in figure 4a for the weights $w_1 ... w_m = 1$ [96]. This approach copies basically the functionality of a human neuron. Several inputs (e.g., touch sensitive receptors in the skin) produce several input stimuli for the human neuron. If the sum of the stimuli exceeds a certain threshold the neuron fires and communicates the human brain a real touch stimulus. The perceptron is designed the same way, copying the human neuronal functionality. To be more flexible, in 1957 *Rosenblatt* et al. introduced adjustable weights between the stimuli inputs and the summation of the stimuli inputs. Those weights are actually the key for the main functionality of NNs, as the learning process mainly is the process of adjusting those weights. The information of the NN is coded in the weights once the training procedure is over, philosophically considering the weights the soul of the NN. The weight adjustment can be implemented by any type of feedback loop, illustrated for the simplest case in figure 4b. The feedback in this case is binary. Further improvements led to the Adaline approach, introduced by *Widrow* et al. in 1960 [97]. For this implementation, the step-like activation function from figure 4b has been replaced by a linear activation function, shown in figure 4c. This step gives some more

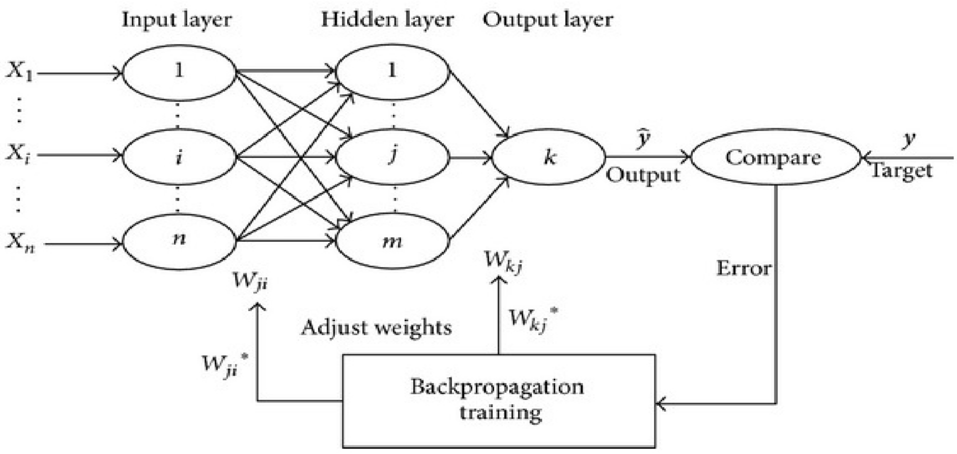


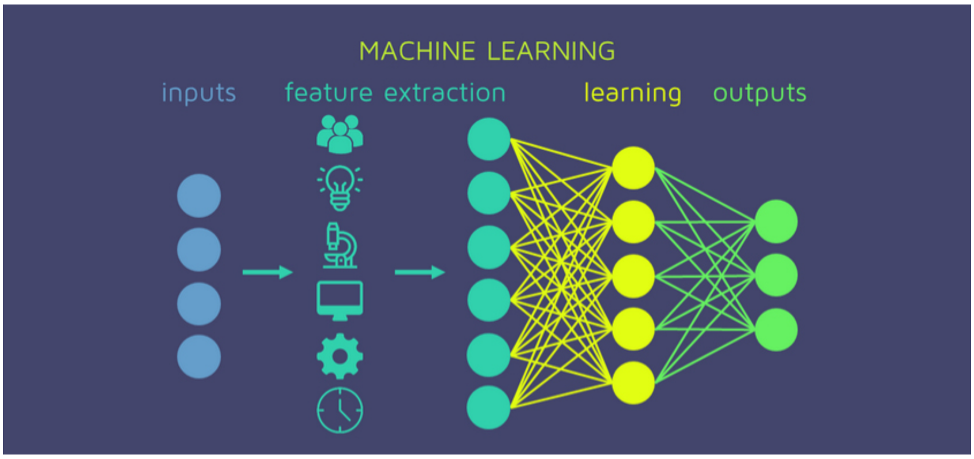

**Fig. 5 Illustration of Backpropagation for Weight Adjustment [99, 100]**

It can be seen, that by means of decision functions feedback to neurons in early process steps is given based on output results. The art is to develop algorithms and approaches, what those output related functions are and how the weights are adjusted. For further reading at this stage the already mentioned collection of books covering this topic may be recommended again [90–94].

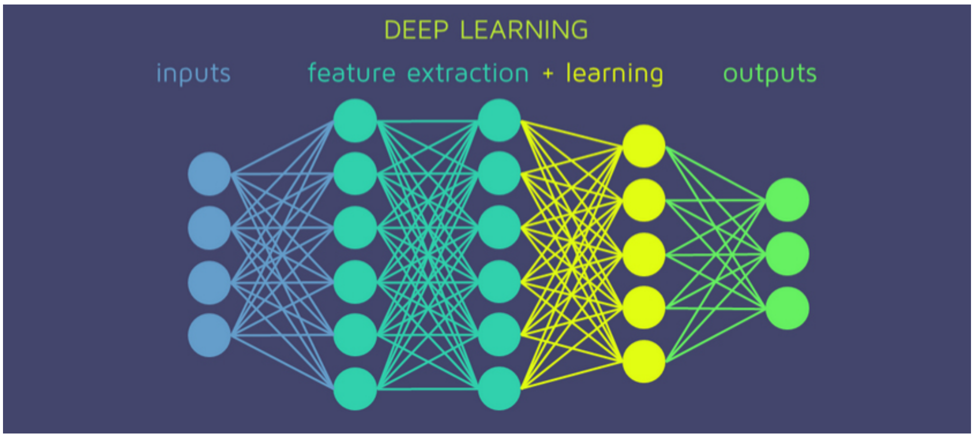
What else can be seen is, that already some kind of layer based approach is implemented here. Three types of layers are existing: input layer, hidden layer and output layer (cp. Fig. 5 and Fig. 6). The input and output layers are the interfaces to the environment. The input layer may, e.g., be connected to a digital camera and each property of the individual pixel acts as an input (e.g., RGB-color values, intensity, brightness, …). This information is processed in the hidden layers (which name insinuates the non-connectivity to the environment) and finally fed to the output layer, which is again the interface to the environment. The individual outputs might code information gathered from the processed data, e.g., input: red, round, smooth surface -> output: tomato [2]. To repeat, the link between those input patterns and output patterns is coded by the weights within and between the hidden layers and is generated in a training phase of the NN. Each network needs to be trained by representative input patterns and can be used for the purpose it has been developed for (simplified said). One can imagine, that the content of the input pattern may be of huge variety, e.g., data base entries for beer recipes, graphical representations, data from market data collection, brewing process parameter, sensor values etc. Based on the nature of the input pattern, according output patterns may be created, e.g., selecting the most popular beer recipe, identify similarities of beer recipes, optimization parameters for the brewing process, measures for improving product development for local markets etc. That way, the huge variety of different applications of AI presented in Section 4 may be more explainable to the reader accepting this fact.

flexibility for the weight adjustment, while modifying the neuron further and increasingly deviating from the original template, the human neuron. Further implications and details about their steps can be found in [98].

A next logical step to further develop the functional progress of the NN is to introduce methods and develop strategies to include interaction of the whole set of neurons in an NN rather than only working with one neuron. Figure 5 illustrates the backpropagation approach introduced by *Rumelhart* et al. [99, 100].




(a) Illustration of a NN structure for Machine Learning [101]




(b) Illustration of a NN structure for Deep Learning [101]

**Fig. 6 Illustration of a Multi-Layer Neural Network [101, 102]**

Figure 6 illustrates the structure of a network of neurons building an NN [101].

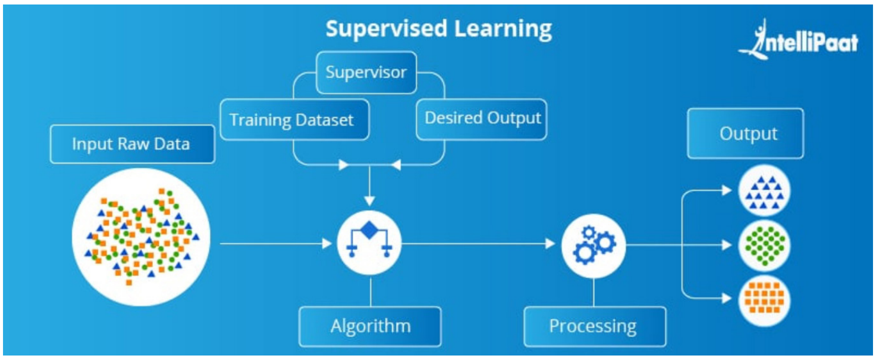
As a side effect, figure 6 also illustrates the difference between Machine Learning (ML) and Deep Learning (DL) [101, 102], which are both specific implementations of AI besides, e.g., support vector machines [103], k-means clustering [104], genetic algorithms [105, 106] or combinations of various [107]. The interested reader may be recommended [89, 91, 93, 94] for further reading as well. The mentioned examples of AI algorithms are, of course, not exhaustive. It can be seen, that both terms are not that different, while as well not identical. ML demands a manual extraction of features of the source data set, making it impossible to work with unstructured data. Skilled human engineers being familiar with the target domain are needed for the feature extraction. DL, on the other hand, is capable to also extract features from any data – on the cost of higher computational cost. Which method is finally used depends heavily on the problem to be solved and the target hardware to be used.

In this section, the basic building bricks of NNs in the context of AI have been introduced to foster a basic understanding of the NN architecture. In Section 2.4 various common Learning Paradigms are discussed briefly. Illustrative examples again can be found in [2].

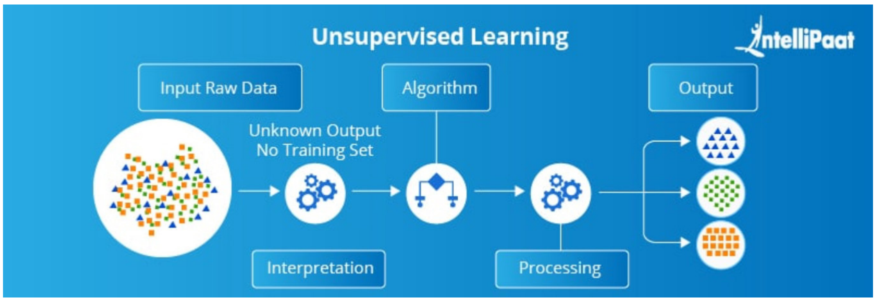
## 2.4 Learning Paradigms

Figure 7 provides an illustrative overview of the main different learning paradigms used in AI applications [108].

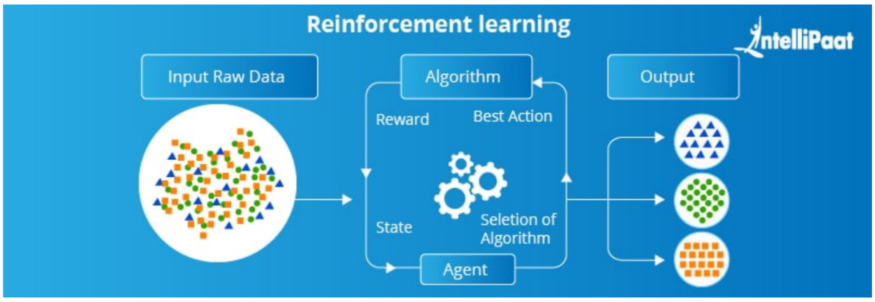
As can be seen, the main existing paradigms are Supervised Learning (SL), Unsupervised Learning (USL) and Reinforcement Learning (RL). A comprehensive summary can be found in [108] and, of course, in [90–94]. Now, let us go into more detail.




(a) Illustration Supervised Learning [108]




(b) Illustration Unsupervised Learning. [108]




(c) Illustration Reinforcement Learning. [108]

**Fig. 7 Overview of the Different Types of Learning [108]**

As illustrated in figure 7a, SL is comparable to the situation, where a teacher guides a student to the correct answer. The teacher will give advice and tell the student, if a result is correct or not. Based on the advice, the student learns the correct answers. If future problems with similar structure occur, the student now knows how to solve it. Similarly, object detection, e.g., detection of vehicles on the road in autonomous driving, may be a starting point. Involving some training data, where specific objects are marked as those specific objects, the algorithm is taught to identify the marked objects as such. The teacher in this case is a data engineer labeling the objects (and therefore creating structured data) in images, providing the reference for the algorithm. In the brewing industry, the input might be electrical patterns from e-noses which are able to detect certain molecules. A specific set of molecules may be classified as a specific off-flavor of the beer. A real example of this automated off-flavor detection using AI can be found in [68].

USL, sketched in figure 7b, instead, does not rely on structured data and as well no labeling of the initial data, therefore, does not have a teacher, a supervisor. USL is a type of self-organized learning that helps find previously unknown patterns in data sets without pre-existing labels [108]. USL algorithms extract similarities from the input data and perform clustering of the results. While SL allows classification of individual detected objects, USL in its original version does not. One advantage of applying USL, obviously, is that no labeling of data is needed for operation. The main application is situations, where unknown similarities, correlations, causalities, or patterns shall be identified. In the brewing or related context, one application may be the analysis of data bases of recipes [12, 34, 35, 44]. The algorithm may find out, that recipes with "IPA" in the title typically include a greater amount of special hop than lager beers … and the hop often is added to the whirlpool. This similarity allows the USL algorithm to cluster those types of recipes. The clusters might afterward be labeled manually, allowing a two step, efficient classification of the initial date.

RL, illustrated in figure 7c, is mainly developed and used for use cases, where the algorithm shall react on its environment on its own, being based on any kind of interaction with the environment. A toddler, e.g., is going to start walking. Gravity and the flow of movements along with the sequence of muscle activation will make the toddler fall to the ground very often in the first stage. After a while, the toddler learns to deal with the gravity (along potentially with different surface condition) by adopting the sequence of muscle activation. Step by step, the toddler learns walking – by adopting its behavior to the environmental feedback (falling to the ground). More specifically, the toddler receives positive feedback, if a movement contributes to the final target "walking" and negative feedback, if the movement is not constructive. Muscle movements triggering positive feedback, also called reinforcement, will be kept, while non-constructive muscle movement sequences will be omitted. Basically and more generally speaking, the RL paradigm is a trial-and-error approach. No predefined input data is needed, no supervision is part of the game. A brewing industry example could be the optimization of the brewing process [72]. In this case, the output of the brewing process might be not as desired. The RL algorithm tries a step into the right direction, adopting the recipe and repeating the brewing process with the adopted setting. If the result is closer to the final target, the change is kept – if not, it will be undone and a new cycle starts. More pictorial speaking, for a human brewer it might be obvious to add more hop, if the level of bitterness is not as desired – because he had learned it or has been taught to do. The machine does not know – as long it had no chance to learn it. Once having gained the information, e.g., by RL, the capability obvious for the human is part of the "skill-set" of the specifically trained algorithm, which that way became "intelligent".

This essentially concludes the elaboration of the technical basics for creating an AI based system architecture beign able to perform specific tasks. Before more details about real applications of this methodology is given in Section 4, in Section 3 some more specific details about approaches for creating input data for the AI system will be discussed, as those "sensing" parts built a crucial back-bone of the system.

## 3 Smart Technologies for the Brewing Industry

The "sensing" element of the intelligent system introduced in Section 2.1 is a crucial part of the overall implementation. As well, various fields from checking raw material from the agrifood sector [69, 109] via the development of an Internet of Beer [110] – ajar to the Internet of Things – towards molecule detections [57] or social media output usage [41] are covered and influenced. Novel use cases of e-noses for digital agriculture, food, and beverage applications have very recently been reviewed in [70]. In this section some essential technologies are introduced which are used to enhance the brewing industry widely – in addition to classic sensors with their immense influence in current production environment, of course, which shall not be intrinsic part of this work. The interested reader might be recommended the literature in [111–117].

### 3.1 Electro-Chemical Sensors for the Beer Industry

Two of the most important sensing devices for the brewing industry are so called e-noses and e-tongues. Both devices are mainly and originally based on semiconductor materials, which are able to detect individual volatile molecules in gas (e-nose) or non-volatile molecules in liquid (e-tongue). The research of e-noses can be traced back to the year 1993 for the brewing industry [57], while still today research is widely going on and e-noses are further developed [118]. The classical starting point for investigations has been set by *Gardner* in that field [57, 87, 119], also extending the search for application fields for the e-nose further, e.g., for classifying coffee and lager beers [120]. Obviously, the e-nose technology is nothing brand new, but has been existing for like 30 years now in the relevant field. Still, there is both room for improvement and reasons for further research today, both for the underlying hardware technology needed for e-noses and as well for the algorithms shaping and processing the sensor outputs.

Improvement of accuracy in beer classification using transient features for e-nose technology, e.g, is described and researched in [121] and mining feature of data fusion in the classification of beer flavor information using e-nose and e-tongue are treated in [58]. A recent comparison of different methods surrounding Near Infrared Spectroscopy, e-nose, and e-tongue is elaborated in [122], while recent progress in e-noses for fermented foods and beverages applications is discussed in [123].

Of course, besides the usage of classical instrumentation approaches along with established and to be developed hardware solutions or base technologies, AI is heavily used in this field and is gaining momentum in the past years. Already in 2003 the prediction of beer flavors from chemical analysis using AI has been researched [63]. As well, in [88], e.g., a comparison of AI methods for classification based on signals from e-nose sensors is given. The application of AI, especially using NNs, in that field is as well discussed and evaluated in [124] and [68], while a concrete implementation for detection of commonly known and typical off-flavors of beers has been carried out and discussed in [125]. As a result, detection accuracies of around 95 % of typical off-flavors like diacetyl could be reached, even using a simple low-cost e-nose – thanks to smart NN based AI algorithms.

Top-level classification of beer styles based on flavor profiles using e-nose, e-tongue and AI has been discussed in [126] and as well in [127] referenced by [128]. Besides the algorithmic potential for improvement of e-nose and e-tongue sensor performance, obviously, also material science is facing room for improvement, as publications from 2023 in that field demonstrate [129– 131]. While [129] specifically elaborates on the potential of different diacetyl perception using metal-oxide sensors in real-time analysis of beer samples [129], in [130] the potential of biotechnology for e-noses is discussed in general and in more detail. Types of biotechnology to be applied and as well biomaterials potentially suited for e-nose applications are investigated and analyzed. Finally, very recent research proposes the usage of hybrid transistors – being partially and classically based on semiconductors and extendedly now enhanced by biotechnology [131]. The latter opens a wide span of future links between chemistry, biology and technology – especially AI – prospecting interesting future applications in the brewing industry.

This concludes the summary about electro-chemical sensors used to enhance the brewing industry. Still, other sources of data to be processed by the described systems to enhance brewing equipment may not be neglected.

### 3.2 Other Sensors used in the Brewing Industry

Apart from the aforementioned electro-chemical sensors, further development of spectroscopy – may it be Near Infrared or Mass Spectroscopy – enhanced by (not only) AI is worth mentioning and target of current research as well, e.g., evaluated in [132] for the brewing process optimization and in [133] for generic lab tasks. Beyond this, haptic sensors and digital cameras as well act as sources for sensor data, e.g., discussing the mouth-feel of beer based on haptic sensor data [51] or for instrumental classification of beer [55]. Talking about cameras, biometric analysis of human reaction on beer consumption is also a topic (e.g., [134] related to [59]). The reaction of the human is used to derive un-biased and direct feedback to the beer perception and preferences.

Finally, virtual sensors may not be forgotten, which may either be a result of the fusion of individual sensors, or data from sensors, which in fact are not sensors in the narrow sense. The latter refers to data created from customer feedback, social media comments to be analyzed, number of sales in local geographic beer markets, popularity of certain beer recipes in online data bases etc. All those are not classical technical sensors, but – as described in Section 2.1 – may be used as the sensing part for the process control loop or cycle.

Those final remarks close the summary about modern sensors and "sensors" potentially being used in the brewing industry. Finally, in Section 4 more concrete real applications currently on the market or under recent research are listed and each discussed briefly.

## 4 Real Applications

There are infinite ideas for applying combinations of the previously presented technologies in the real industrial field. A selection of current usages is given in this section. An overview of how to brew beer with AI is discussed by [12], commenting and discussing some recent topics in the beer industry where AI is used to improve distinct parts of the production process. Similarly, [2] provides a popular scientific quick insight into the topic. In [13] *Jason Lambert* discusses the future of beer in the context of digitization.

One of the most popular, while from the author's perspective least creative one, is the creation of beer recipes using ChatGPT or other generative AI based platforms and algorithms [24–32]. This includes companies like Beck's (while their Autonomous Beer was a PR gag and included also design and marketing components enhanced by AI), Atwater Brewery, Champion Brewing, Kensington Brewing Company, Santiam Brewing, Whistle Buoy Brewing Company (Victoria Brewing), Rio Bravo Brewing Company, Dainton Brewery, Grain Bin Brewing Company, or Modus Brewing. There are meanwhile competitions to find out, which generative AI produces the better beer [79].

For the optimization (e.g., of the brewing or fermentation process) and application locally in craft breweries or hobby brewer environments, low cost platforms equipped with AI can be used [18–23]. All of those are based on the open source platform RaspberryPi. The platform BreweryPi developed from a project of the company Deschutes Brewing Bend, Oregon [18, 19]. In this project, an AI driven implementation was built, allowing the company to automate and optimize the fermentation process, leading to cost savings of almost one million US dollars short term to the delayed need for an additional chiller during the fermentation process, keeping the production output constant.

Recipes not only may be created, but also analyzed, checked for similarities and further used in the brewing process [33–39]. Companies having tried this approach includes Deep Liquid, Night Shift Brewing, Moncton Brewery, Mikrobrauerei MNBrew (with HSLU Luzern), or Barossa Valley Brewing. One approach is using recipes for bread, still, the methodology using AI in that field may be transferred to beer as well [35]. Given the possibility to scan recipes from the internet, why not scan complete markets? One approach in this field is to analyze the Italian market on consumer preferences for craft beer to check, if there is additional market potential [41]. "Towards crafting beer with AI" is the business and research motto in [34].

Generally speaking, using AI for marketing in the beer industry is even more widespread [24, 41–43]. In some cases, even customer feedback is included, potentially directly influencing the brewing process [28, 37, 44–47]. While IntelligentX, a startup founded in 2016, is meanwhile bankrupt, the main idea is still a promising approach. Based on customer feedback, both directly and using a messenger bot for automated social media analysis, the acceptance of the beer along with customer acceptance is recorded and analyzed. The gained information is further used to adapt the brewing process to achieve the best beer fit for the target market, reaching highest customer acceptance and consequently pushing the business forward.

Talking about marketing and customers: why not to use AI as a recommendation system, as a digital beer sommelier [48, 49]? In those cases, a digital beer recommendation system has been implemented, following the knowledge and approach of a human beer sommelier. The customer may be recommended a beer online based on local availability, personal preferences, and the context of the beer consumption (e.g., food pairing). To take the next step, it would be possible to create automated beer reviews based on some catchphrases [50].

If it comes to design, e.g., of the beer label or the marketing campaign, mainly defining the image of the beer product, also AI may support [24, 28, 32, 40]. Beck's and Modus Brewing, e.g., designed the style of their beer bottles and cans using AI.

Overall, research and phantasies about new complete business models arise [14, 15], e.g., the idea of a small scale production equipment for individual beer brewing [14]. One of the indirectly created new business models is the field of consulting in the beer industry, e.g., on optimization of the brewing process and other bricks in the production chain [17].

Coming to image processing using AI some more fields of application arise. First, the quality of beer in the context of foam stability can be automatically controlled by building a robotic pourer, which allows beer handling (pouring) in a repeatably and standardized way [52]. A first application of the so developed RoboBEER pouring robot [52] is to search for correlations between recorded and classified foam stability in conjunction with the measurement of relative protein content and composition in the underlying beer [54]. In both cases [52, 54] computer vision and pattern recognition is used to achieve the desired experimental setup and output. The target is as well to use ubiquitous materials and openly accessible low cost hardware and sensors. A side effect is, that for a fixed chosen beer, by applying a predetermined pouring process, beer with constant foam stability and shape can be served to a customer as well. This leads to a next application of AI in this context, when the described hardware and software setup is extended by biometrical analysis enhanced by AI technology [53, 135]. In [134] related to [59] a remote sensory assessment of beer quality based on visual perception of foamability and biometrics is introduced as a continued development of [53] and [135], allowing to derive beer acceptance and preference based on human mimic and body language. The same research group in further consequence has also researched and developed a low cost e-nose to assess aroma profiles using low cost hardware and AI [61, 62]. The latter system is used to perform a beer aroma and quality traits assessment using AI [60] and is further used very recently in combination with [134] to identify the effects of different beer compounds based in biometrically assessed emotional responses in consumers [76]. A research group from KU Leuven is performing research in a similar direction by using AI and ML to predict beer flavor and guide product development [15, 136]. Going one step beyond biometrics, there are research targets to include the human perception in the beer production process, by creating an intelligent olfactory system based on AI [77, 78]. This research is performed at the Campus of Senses, a collaborative project between the Fraunhofer Institute for Process Engineering and Packaging IVV and the Fraunhofer Institute for Integrated Circuits IIS, with the involvement of the Friedrich Alexander University Erlangen-Nuremberg as a university partner, focusing on research into chemosensory sensory perception – smell and taste – and their transformation into technically mechanical and digital concepts [137].

In the context of both industrial and scientific analysis of beer quality, several fields can be identified, where AI and sensing hardware, like e-nose and e-tongue, implement an automated quality management system. Sources can be found, e.g. to report beer quality based on the mouth-feel of beer, which is an essential criteria to satisfy the customer influencing the drinkability (and consequently the number of sales) [51–56]. Like with other related fields, this research and topic seems to bother the community long since and still now, as there is one publication from 1991 [51] and at latest two from 2023 [55, 56]. A similar observation may be made focusing on the flavor analysis of beer, treated in [15, 57–63]. As well here, the span of relevant papers starts in 1993 [57] and seems not yet to finish in 2023 [15, 63]. Flavor is of course closely related with off-flavors, caused by beer faults. This specific topic is again researched by a group from Australia (cp. RoboBEER) in [68]. Raw materials, obviously, contribute significantly to the beer quality as well. Therefore, as a consequence including the analysis of the latter in the quality management process is a no-brainer, while approaches using AI are introduced in [69, 70], both from the current year 2023. There can be also applications found in research and practice, which focus on the brewing process [71–73] or an intensified view and focus on the fermentation process [18, 22, 64–67]. The Kirin Brewery, Tokyo (Kirin Holdings) is a prominent representative of this approach. As well, Deschutes Brewing Bend, Oregon, implemented an AI based system optimizing their brewing and fermentation processes. Cost savings of 8 million US dollars were the result on the long term ([138]). Another real world example in this context can be found with Sugar Creek Brewing, where as well the brewing and fermentation process is smartly monitored. Additionally, using USL based AI, mistakes in the brewing and filling process could be identified, leading to less losses due to bottles over-foaming. This led to a cost reduction of 30,000 US dollars per month. Again in this context, the topics have been treated long since, starting with a publication from 1995 [64] and showing still many contributions in 2023, including further enhancements based on new and today affordable sensing and signal processing platforms, involving AI as a supporting vehicle [18, 22, 71, 73]. A pure lab based setup is followed in the Carlsberg Fingerprinting project, where automated analysis and recipe adoption within the Carlsberg Lab has been fostered to enhance and speed-up the product development process [74, 75]. The project has been carried out in cooperation with Microsoft. The top-notch research currently is presumably the inclusion of first biometrics in the quality definition and analysis process – and, for sure, second the consideration of human cognitive system responses [76–78]. This enables to serve the human centric approach as one of the main pillars of industry 5.0 as defined by the European Commission [139]. As discussed in [140] and in the literature review in [141], instead of taking technology as the key player of the next industrial revolution, having been the focus in industry 4.0, three different key drivers are set as the center of the industry 5.0 paradigm by the European Commission [139].

- The human-centric approach, which places human needs at the heart of the production process, asking what technology can do for workers and how can it be useful [141].
- Sustainability, which focuses on reuse, repurpose, and recycle of natural resources and reduce of waste and environmental impact [142, 143].
- Resilience, which implies an introduction of robustness in industrial production. This robustness provides support through flexible processes and adaptable production capacities, especially when a crisis occurs [144].

As provided in an overview-like presentation in [145], besides the technical challenges, also ethical issues are being discussed in the industry [146, 147], influence of industry 5.0 on the companies' culture(s) [148] and non-technical processes [140] like marketing as studied in [149]. Also, industry 5.0 does not only influence the companies and their employees, but will have significant impact on the whole society [140], e.g., describing and analyzing the correlation of consequences of "Smart Manufacturing" towards a "Digital Society" [150, 151]. This investigation shows the complexity of the industry 5.0 movement on the one side and the huge influencing potential, the immense scope of the latter on the overall society, on the other side.

This is as well the focus and core topic of the LEONARDO Erasmus+ project currently ongoing, where two beer manufacturing test plants are developed [16, 152]. The LEONARDO project aims to transform Industrial Engineering and Management (IEM) education by establishing innovative teaching methods, materials, and tools with a human-centric approach in the context of the industry 5.0 paradigm. In practice, the project will leverage an industry 5.0 replica of a brewing system as a hands-on learning environment for

IEM students. LEONARDO will thus foster the entrepreneurial skills of IEM students by providing an applied learning environment to develop and test ideas. The brewing system called LEAF (= Learning and Experimenting open-Access Factory) will facilitate innovative learning approaches as well as new teaching methods [153].

## 5 Discussion

Recapturing this article clearly shows, that AI is to be considered a useful tool for beer production environments. As well, it is not considered only since yesterday, but omnipresent and relevant at least since the early 1990s. Being a controversial topic, skepticism of consumers, breweries and beer experts needs to be respected, while every technology is as good, bad, or malicious as the applicant or user of the technology is. The technology is there to implement supporting measures, improve quality cycles and beer quality – by still keeping or even increasing beer variety on the market. The latter is possible by AI techniques described, which include the consumer into the production process. The author of this article supports the hypothesis to be careful using AI (not: "throwing" it on each and every problem without thorough re-consideration), but as well is optimistic, that used in the right way the technology can bring back focus on the human, using AI technologies in an industry 5.0 like human-centric approach. Industry 4.0 was all about the development of technologies being able to perform tasks, while industry 5.0 focuses more on how to use these technologies to serve the human being. The technology shall be made the humans' servant, not the opposite way.

## 6 Conclusions

This article delivered a comprehensive state of the art analysis, on how AI may and does support the brewing industry. It turned out, that AI may be used in a manifold of fields, starting from the design of recipes, via the automated quality management of raw materials, towards observing, controlling, optimizing the whole brewing and production process of the product, potentially even involving the customer into the process by integrating direct and indirect customer feedback. Obviously, the topic is highly interdisciplinary and requires experts from various disciplines working together closely to achieve the best results. For a better understanding of the AI technology, a top-level system architectural presentation of the latter has been given as well, to more simply allow the average brewing community member to follow the real world applications presented at the end of the document. While AI has been used long in the past of the history of beer brewing (since more than 30 years), the end is not yet reached, proven by the manifold of publications in recent years. The coming years, along with more maturation of advanced AI technologies, will for sure develop interesting and teasing possibilities. Times remain exciting!

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### Conflicts of interest

The authors declare no conflicts of interest.

### Abbreviations

The following abbreviations are used in this manuscript:

- AI: Artificial Intelligence
- DL: Deep Learning
- IEM: Industrial Engineering and Management
- ML: Machine Learning
- NN: Neural Network
- RL: Reinforcement Leanring
- SL: Supervised Learning
- USL: Unsupervised Learning

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