Applications of Artificial Intelligence (AI) in Cannabis Industries: In Vitro Plant Tissue Culture

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Abstract: - This review paper highlights the application of artificial intelligence (AI) in Cannabis industries. Growing Cannabis especially on a large scale can come with several complex challenges unique to the industry**.** Therefore, artificial intelligence (AI) has been implemented across all stages of the Cannabis supply chain. Artificial intelligence (AI) is a powerful tool that can be applied in all aspects of the Cannabis industry. However, developing an effective artificial intelligence (AI) model is a challenging task due to the dynamic nature and variation in real-world problems and data. In addition, a growing number of artificial intelligence (AI) -powered apps, Chatbots, and websites are launching to help medical Cannabis (marijuana) customers to find the products. Artificial intelligence (AI) and machine learning (ML) have become essential to Cannabis businesses that want to display the most relevant products and services to consumers when they visit companies websites. Digital medical Cannabis represents the combination of a Cannabis product and a second- generation Artificial intelligence (AI), system to create a new intellectual property (IP). With medicinal and recreational interests for *Cannabis sativa* L. growing, research related to the optimization of in vitro practices is needed to improve the current methods. Plant tissue culture experiments comprise a part of very complex studies with many problems. In plant tissue culture studies, optimization is highly desirable and the application of new computational approaches like artificial intelligence (AI) and machine learning (ML) algorithms using fewer inputs is on the rise in recent years. It has been shown that **Generalized Regression Neural Network (GRNN)** as one of the most powerful of ANNs has more accuracy than other artificial neural networks (ANNs) in modeling and forecasting in vitro culture procedures.

Key Words: Artificial intelligence (AI), AI-Chatbot, Cannabis industries, Generalized Regression Neural Network (GRNN), Machine learning (ML), Plant Tissue Culture.

I. Introduction

Cannabis sativa L. (Family: Cannabaceae) is reported as one of the oldest cultivated crops for various purposes such as food, medicine and fiber (1-14). *Cannabis sativa* L. can be divided into Medical *Cannabis sativa* (Marijuana or drug type) containing very high levels (1 to 37%) of psychoactive molecule, Δ9-Tetrahydrocannabinol (Δ9-THC) drug or and 'Industrial *Cannabis sativa* known as hemp based on the tetrahydrocannabinol (THC) (0.3%) contents (1-14, 104). Hemp is a genuine factory for the synthesis of secondary metabolites such as flavonoids, alkaloids, phenolics, and lignins, all of which possess high economic values (1-14). Hemp fibers and seeds are used as an important raw materials for several industries such as textile, papermaking, automotive, oil, biofuel, construction, pharmaceutical and cosmetics (1-14). However, due to the presence of psychoactive molecule, tetrahydrocannabinol (THC) compounds such as Λ9-tetrahydrocannabinol (Λ9-THC) and Λ8-tetrahydrocannabinol (Λ8-THC), its cultivation and use is restricted/regulated in many countries (1-14, 104). Apart from the highly disputed medicinal purposes, hemp seeds are used as food and nutritional products in various cultures around the world (1-14). Similarly, the oil obtained from the hemp seeds is used as edible oil and other purposes. One of the main industrial use is the production of high quality fiber from the stem bark used in textiles, clothing, papers, building materials and bio-fuel (1-14, 103).

Legalized use of Cannabis products and the rising interest in their therapeutic benefits have opened up new opportunities for therapy and marketing (1-16, 104). However, the marked variability in formulations, administration modes, therapeutic regimens, and inter- and intra-subject responses make the standardization of medical Cannabis-based regimens difficult (1-25, 102). Legalization has made the Cannabis market highly competitive and lowered the revenue margins (1-20, 102-104). The development of tolerance toward Cannabis and low adherence to chronic administration further impaired its long-term beneficial effects (1-16, 102, 103). Therefore, new technologies have benefitted from the development of many fields such as information technology, engineering, instruments and the methods of analysis, and material science (14-30, 103).

Artificial intelligence (AI) is a broad field of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence (14-102). Artificial intelligence (AI), Machine learning (ML), and deep learning (DL) are three prominent terminologies used interchangeably nowadays to represent intelligent systems or software (14-60, 103). Artificial intelligence (AI) has become an important area of research in virtually all fields: virtual painting, traffic signal detection, sarcasm detection, engineering, science, education, medicine, business, accounting, finance, marketing, economics, stock market, law, agriculture including Cannabis industries (14-50, 94-102). Artificial intelligence (AI) has played an important role in agriculture including Cannabis crop management (94-103).

Artificial intelligence (AI) is a powerful tool that can be applied in all aspects of the cannabis industry (94-103). New technology can help the cultivators to produce better crops and identify the right times to scale their growing operations (94-103). For suppliers and sellers, AI and IoT technologies can also create more accurate demand predictions, so that, they can avoid being out of stock on the wrong products and eliminate slow-moving inventory for good (94-103). Therefore, future of Artificial intelligence (AI) and the Cannabis inventory will be controlled by the AI software to support more aspects of Cannabis operations, from content marketing to sales (94-103).

Following sections updated and discussed about the applications of Artificial intelligence (AI) in Cannabis industries including in vitro studies (14-35, 103).

II. Artificial Intelligence (AI) : Definition and Meaning

Artificial intelligence (AI) is a broad field of computer science concerned with building smart machines capable of performing tasks that typically required human intelligence (14-50). The father of Artificial Intelligence, John McCarthy, in the 1990s defined Artificial Intelligence as *"Artificial Intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs"* (14-50, 103). In other words, Artificial Intelligence (AI) is intelligence shown by machines. In computer science, the field of Artificial intelligence (AI) defines itself as the study of "Intelligent agents (14-50, 103). Artificial intelligence (AI) is also defined as a branch of information technology that allows the programming and design of both hardware and software systems capable of providing machines with certain characteristics considered typically human, such as, for example, visual, spatio-temporal and decisional perceptions (14-39). The primary goal of Artificial intelligence (AI) is to enable computers and machines to perform cognitive functions such as problem-solving, decision making, perception, and comprehension of human communication (14-50, 103). Artificial intelligence (AI) is a leading computer technology of the current age of the Fourth Industrial Revolution (Industry 4.0 or 4IR), incorporating human behaviour and intelligence into machines or systems (14-53). Artificial intelligence (AI)-based computer modeling is the key to build automated, intelligent, and smart systems used to solve day to day problems (14-60, 103).

Various types of artificial intelligence (AI) such as analytical, functional, interactive, textual, and visual Artificial intelligence (AI) can be applied to enhance the intelligence and capabilities in real-world application areas including business, **traffic recognition system** using machine learning, **virtual painter** using Artificial intelligence (AI) (23, 24) and Opencv, finance, healthcare, agriculture, smart cities, and cybersecurity (14-60). Three key terms *Automation*, i.e., reducing human interaction in operations, *Intelligent*, i.e., ability to extract insights or usable knowledge from data, and *Smart computing*, i.e., self-monitoring, analyzing, and reporting, known as self-awareness, have become fundamental criteria in designing today's applications and systems in every sector of our lives (14-60, 103). However, developing an effective Artificial intelligence (AI) model is a challenging task due to the dynamic nature and variation in real-world problems and data (14-50, 103).

Further there are different categories of Artificial intelligence (AI); 1) Analytical AI. 2) Functional AI. 3) Interactive AI. 4) Textual AI. and 5) Visual AI (14-60, 103). To build AI-based models, AI techniques are classified into 18 categories: (1) Reasoning. (2) Artificial life. (3) Belief revision. (4) Constraint satisfaction, and theory of computation (5) Data mining. (6) Programming. (7) Genetic algorithms. (8) Knowledge representation. (9) Machine learning. (10) Neural networks and Deep learning. (11) Knowledge discovery and Advanced analytics; (12) Rule-based modeling and Decision-making. (13) Fuzzy logic-based approach. (14) Knowledge representation, uncertainty reasoning, and Expert system modeling. (15) Case-based reasoning (16) Text mining and Natural language processing. (17) Visual analytics, computer vision and Pattern recognition (18) Hybridization, Searching and Optimization (14-60). These Artificial intelligence (AI) based techniques can play an important role

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in developing intelligent and smart systems in various fields including Cannabis industries (14-60). Artificial intelligence (AI) -based modeling which is considered as a key component of the fourth industrial revolution (Industry 4.0) (14-60). It begins with research motivation and proceeds to AI techniques and breakthroughs in many application domains (14-50). Overall, Artificial intelligence (AI) techniques have proven to be beneficial in a variety of applications and research fields, including business intelligence, finance, healthcare, visual recognition, smart cities, IoT, cybersecurity, and Cannabis industries (14-60). In particular, machine learning algorithms have been proven to be capable of dealing with complicated medical data such as ECG signal data, where they showed some outstanding results compared to traditional statistical approaches (14-50, 103). These studies suggested that machine learning (ML) can provide medical research with powerful techniques beyond the traditional statistical approaches mostly used, which include the conventional statistical tests, linear and logistic regression (14-50, 103).

The emergence of artificial intelligence (AI) has significantly improved almost every aspect of human life, considering the enormous roles it has begun to play in agriculture, researchers and scientists are seeking better ways of improving and ensuring optimal efficiency of the developed systems (14-50, 103). The range of Artificial intelligence (AI) has grown enormously to the extent that tracking proliferation of studies becomes a difficult task (14-50, 103). In the last few years, there has been an arrival of large amount of software that utilizes elements of artificial intelligence (14-50, 103). Subfields of Artificial intelligence (AI) such as Machine Learning (ML). Natural Language processing, Image Processing and Data mining have become an important topic for today's tech giants (14-52, 103).

Artificial intelligence (AI) applications in education have received a lot of attention in the last couple of years (14-50). The field Artificial intelligence (AI) originates from computer science and engineering, but it is strongly influenced by other disciplines such as philosophy, cognitive science, neuroscience, and economics (14-51). In general, given the interdisciplinary nature of the field, there is a little agreement among Artificial intelligence (AI) researchers on a common definition and understanding of AI and intelligence (14-50). Artificial intelligence (AI) and Machine learning (ML) are often mentioned in the same breath (14-50). Machine learning (ML) is a method of Artificial intelligence (AI) for supervised and unsupervised classification and profiling, for example to predict the likelihood of a student to drop out from a course or being admitted to a program, or to identify topics in written assignments (14-55). Machine learning (ML), actively being used as a branch of Artificial intelligence (AI) and is defined as the study of computer algorithms that improve experience automatically (14-50). The development of Machine learning (ML) technique is very fast now (14-50). Its usage has spread to various fields, such as learning machines currently used in medical science, pharmacology, agriculture, archaeology, games, business and Cannabis industries (14-52).

III. Applications of Artificial Intelligence in Cannabis industries

The increase in strength of THC-plants composition is related to legalization, globalization, pharmaceutical-related factors (15, 16, 103, 104). The increased use of medical Cannabis for multiple diseases and legalization of its use in many countries have led to the increase in variety of available products (14-17, 103-104). Multiple Cannabis plants and strains and different growth modes, extracts, final formulations, and delivery methods are being promoted (14-17). In addition, distinct batch-to-batch variability further complicated the standardization of products (14-17). The legalized Cannabis market is dominated by high Λ9-tetrahydrocannabinol (THC) Cannabis flower and showed growing expenditures on extracts (16-17). Higher-strength THC has become increasingly available after the legalization of Cannabis (14-16). Cannabis is a highly personalized medicine, which needs to be titrated up (14-17,101-102). The pharmacokinetics of the most Cannabis products is not known. The major cannabinoids are substrates for numerous metabolic enzymes, such as cytochrome P450 metabolizing enzymes (14-17, 103). The PK of oral THC showed marked variability, with differences between formulations, for example, higher variability in baked goods and oil forms (14-17, 103) The preparation method significantly impacts the final product characteristics (14-17, 103).

Considerable differences could be found in annual Cannabis consumption across countries and in inter- and intra-subject variability for the pharmacokinetics of Cannabis formulations (14-17, 94-103). Clinicians also failed to adhere to Cannabis prescription guidelines, further impacting the difficulty in standardizing therapeutic regimens (14-17). These examples indicated the challenges in medical use of these products for both caregivers and patients (14-103). Commonly, the right formulation, preferred dose, and delivery mode are identified and appropriate therapeutic regimens are selected on a trial-and-error basis, rather than on validated data (14-103). Thus, physicians and patients find it very difficult to maximize the beneficial effects of these products (14-103). Therefore, Artificial intelligence (AI) is applied in Cannabis industries in order to solve these problems (14-17, 94-103).

Digital medical Cannabis is a Cannabis product controlled by a second-generation artificial intelligence (AI) system that improved patient responses by increasing adherence and dealing with tolerance (14-60, 94-103). Second-generation artificial intelligence (AI) systems focus on a single patient's outcome and deal with the inter- and intra-subject variability in responses (14-46, 94-100). The use of digital medical Cannabis is expected to improve product standardization, maximize therapeutic benefits,

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reduce health care costs, and increase the revenue of companies (14-75, 94-102). Digital medical Cannabis offers several market differentiators for Cannabis companies (14-70, 94-103).

Digital medical Cannabis represents the combination of a cannabis product and a second- generation Artificial intelligence (AI), system to create a new intellectual property (IP) (14-79, 94-103). This new IP is a profound market differentiator that can help companies to increase their market share. The use of digital medical Cannabis can also generate big data resources with focus on clinically meaningful endpoints and deal with the biases inherent in first-generation systems (14-90, 94-103). This new big data resource type can also serve as basis for a new IP and further improvement in algorithms (14-80, 94-103). Digital medical Cannabis provides advantages to all players in the health care system. While clinicians and patients can enjoy its clinical benefit, drug manufacturers can expect increased sales and the health care system can save in costs (14-90, 94-103).

Cannabis companies benefit from increased market share and revenue by having market differentiators based on improved clinical outcome (103). Maximizing clinical benefits enables the health care systems to save without raising the overall health care budget (14-80, 94-100). In contrast to the most first-generation Artificial intelligence (AI), systems, second generation systems are self-sustained without imposing additional costs (14-90, 94-103). The costs associated with developing and supporting digital systems are charged not to the health care system, but to the increased revenue of drug manufacturers and savings of insurance companies (14-60). Deep Learning (DL) has been described as one of the key subfields of Artificial Intelligence (AI) that is transforming weed detection for site-specific weed management (SSWM) (14-89, 94-103).

According to PWC's Global Artificial Intelligence Study: Exploiting the AI Revolution report, artificial intelligence (AI) could contribute up to $15.7 trillion to the global economy by 2030 and increase the global GDP by 14% (14-103). Already, automation, artificial intelligence, and machine learning are becoming commonplace in the Cannabis industry as more innovative technology is launched across the supply chain (14-79). Artificial intelligence (AI) is impacting the Cannabis supply chain and the primary obstacles of Cannabis businesses face from the growth of automation, machine learning, predictive analytics, and artificial intelligence (14-80, 94-100). Marijuana sales is just one stop on the path from seed to sale where artificial intelligence is having a significant effect (14-79). From speeding up processes, reducing errors, and saving money, artificial intelligence is changing the way Cannabis businesses operate and sell (14-90, 94-103).

In recent years, artificial intelligence (AI) and machine learning (ML) have become essential to Cannabis businesses that want to display the most relevant products and services to consumers when they visit companies websites (14-90, 94-103). When artificial intelligence (AI) is working behind the scenes to match visitors to the items they are the most likely to purchase and displaying those items in real time, sales and revenue will increase (14-80, 94-100). In addition, a growing number of Artificial intelligence (AI) -powered apps, chatbots, and websites are launching to help marijuana customers to find the products they need (14-80). This helps Cannabis businesses improved sales and customer relations online as well as in brick-and-mortar dispensaries and retail locations (14-75, 94-103).

For example, **Potbot** is a mobile app available in Apple's App Store and the Google Play Store that uses artificial intelligence to sort through tens of thousands of Cannabis strains, read peer-reviewed medical journals to analyze studies on cannabinoids, and pair that information with dozens of symptoms, such as asthma and insomnia, to find which type is best to treat the specific condition (14-90, 94-103). **B2B** sales in the Cannabis industry have also changed in recent years due to artificial intelligence, predictive analytics, and machine learning (14-90). As a result, workflows have been streamlined, tasks have been automated, and sales teams can focus more of their time on revenue-generating activities (14-90, 94-103). **Blinx-AI** uses artificial intelligence in its pharmaceutical application to analyze the amount of THC in Cannabis products (14-90, 94-100). The Artificial intelligence (AI) looks for patterns and commonalities between Cannabis strains (14-90, 94-103). This type of data helps medical marijuana patients to understand the levels of active compounds, monitor their dosages, and have more control over their medications (14-90, 94-103).

Another example is **Lucid Green's QR Code technology**, LucidID (14-93, 94-100). Cannabis brands can add a custom QR code to their product packaging that consumers can scan and instantly access information about potency, customer and patient reviews, dosage recommendations, expected effects, batch number, lab testing, and more (14-103). For dispensaries and retailers, **Budster** connects directly with the point-of-sale system and uses artificial intelligence (AI) to assesses the health of the business and determine the true value of each customer (14-90, 94-103). It also provides Artificial intelligence (AI) -generated offers and business insights to increase customer loyalty, sales, and revenue (14-103). For businesses that sell to Cannabis license holders, the Cannabiz Media License Database is the only sales, customer relationship management (CRM), and marketing tool that leverages Artificial intelligence (AI), and machine learning (ML) to help sales people do their jobs more efficiently and more successfully (14-90, 94-103).

There are typically digital sensor-based systems managed by various platforms – **Aroya, Canix** and **Trym** which are few examples– that control lighting timing, lighting intensity, irrigation, temperature, humidity, fans and airflow, CO_2 levels and plant nutrients (14-103). The camera are mounted on a robot, the camera rolls down aisles in a greenhouse at night scanning the plants and then combines the cameras spectral imaging with machine learning (ML) and artificial intelligence (AI) to detect diseases and Cannabinoids directly from the growing plants (14-90, 94-103). This technology creates a 3D model of each plant using 1,000 data points, then combines that with environmental data to see how the plant is progressing (14-70, 94-103).

Artificial intelligence (AI) is already being implemented across all stages of the Cannabis supply chain (14-90, 94-103). For cultivators, tools like Bloom **Automation** and **BudScout** are improving processes and outcomes (14-80, 94-100). Bloom Automation, uses patented artificial intelligence, machine learning, and computer vision to help Cannabis businesses automate many growth room tasks (14-90). For example, the Bloom Automation team created an algorithm to quickly and precisely trim Cannabis branches robotically (14-90, 94-103). **BudScout** helps cultivators to increase sales and revenue by detecting early problems (103). The **BudScout** robot monitors crops on an hourly basis and reports environmental metrics (14-80, 94-100). Using a proprietary algorithm, the technology can detect plant health problems up to 14 days sooner than a person (14-103). In addition, BudScout uses artificial intelligence (AI) to measure the size and quantity of buds on plants and predicts the expected yield many months in advance (14-80, 94-103).

The sales of Cannabis products play an important role in a Cannabis business success. Therefore, it is important to consider how artificial intelligence is affecting investors and risk management in the Cannabis industry (14-90, 94-103). **VantagePoint**, a software company offering programs that predict stock market changes, integrated Cannabis stocks in the United States and Canada into its platform in 2019 (14-80). Using artificial intelligence, VantagePoint identifies patterns in the data that can be used to make more accurate forecasts and investment decisions (14-90, 94-100). Another software, **Adherence Compliance**, which offers a mobile and cloud app for marijuana regulatory and financial compliance (14-68, 94-100). **Adherence Compliance** uses artificial intelligence, predictive analytics, and machine learning algorithms to help Cannabis business stakeholders assess business risk (14-80, 94-100). Businesses operating in the Cannabis industry experience similar challenges when integrating artificial intelligence into their operations as businesses in other industries do (14-80, 94-103).

The three primary challenges are related to people, data collection, data reliability and security (14-70, 94-100). The companies that can successfully navigate these changes will be positioned to exploit the benefits of artificial intelligence, automation, predictive analytics, and machine learning for growth and cost savings (14-80). Furthermore, with new technology, including technology that uses artificial intelligence, there is an employee learning curve (14-80, 94-100). For businesses, this equates to training costs and possibly hiring costs if the required talent is not already on staff (14-60, 94-100). Many companies could see significant training costs as well as unavoidable employee turnover when artificial intelligence technology is implemented (14-60, 94-103).

Artificial intelligence technology requires data in order to successfully integrate it into a business' daily operations (94-100). For many companies, finding the budget to collect, standardize, and effectively index this data is a big problem (14-90, 94-103). However, the benefits of doing so are worth it in the long-term. Data is often only useful if it is current (14-80). However, for many businesses, continuously collecting data to ensure it is reliable for decision-making presents a significant challenge (94-100). In addition, privacy and security concerns add another layer to the complexity of managing artificial intelligence technology used in business operations (14-90). Despite these challenges, artificial intelligence (AI) technology is the future of Cannabis businesses (14-90, 94-103). Cannabis industries have started integrating data into their operations (14-90). This could set themselves up for great success in years to come when competitors that have yet to leverage artificial intelligence technology fall behind (14-90, 94-103).

Artificial intelligence (AI) and machine learning (ML) are becoming critical components of a Cannabis business strategy with good reason (14-90, 94-103). Artificial intelligence (AI) delivers measurable benefits through increased productivity and improved employee decision-making (14-90, 94-103). Furthermore, the data used in artificial intelligence (AI) technology enables businesses to deliver more personalized consumer experiences as well as higher quality products and services (14-80, 94-103). This is true in the Cannabis industry as it is in other industries that leverage the power of artificial intelligence (AI) (14-80, 94-100). Furthermore, if a company has access to artificial intelligence, it has a significant competitive advantage in the marketplace over companies that do not have the same (or better) predictive, real-time data (14-80). Cannabis growers are looking closely at mainstream agricultural technology to gain a new level of precision cultivation that employs everything from artificial intelligence and augmented reality to robots and drones (14-90, 94-103).

The roles played by the application of intelligent systems were highlighted with a view of broadening reasoning and channelling future researches towards developing better and more techno-efficient intelligent systems to aid in Cannabis agricultural related activities (14-80, 94-103). Research findings indicated that technological improvements towards the introduction and usage of Artificial Intelligent (AI) systems will result in a more techno-efficient method for weed detection in Cannabis agriculture (14-80, 94-100). The application of technological gadgets embedded with Artificial Intelligence (AI) in Cannabis agriculture is currently yielding significant results in weed detection and improving crop yield (14-80, 94-103).

In recent years, there have been many exciting developments in the world of Artificial intelligence (AI), including many new automation solutions for crop cultivation processes worldwide (94-103). Naturally, Artificial intelligence (AI) has many applications for the Cannabis industry and can help home growers and enterprise growers alike optimize their profits (94-100). Growing Cannabis especially on a large scale can come with several complex challenges unique to the industry (94-95). For example, creating the right level of humidity and sunlight is key to maximizing production (94-95). Modern Artificial intelligence (AI) technology can help farmers to monitor the conditions of their growing environment and, with the implementation of IoT devices and robotics, implement essential changes as soon as they are needed (94-103). As the growing environment matures and begins to self-regulate, farmers can reduce the likelihood of unhealthy crops (94-95). However, Artificial intelligence (AI) sensors and cameras that detect plant growth rates and other indicators of plant health can help cultivators to detect the sick Cannabis plants before it becomes unsalvageable (94-95). This technology can also help to identify the proper treatment for each plant. Information like this can lead to a massive reduction in waste and increased crop yield (94-95, 103). Artificial intelligence (AI) can also improve Cannabis crops rather than just keeping them healthy. With more accurate insights into their production and the conditions that yield the best results, cultivators can create strains with higher cannabinoid percentages and greater pest resistance (94-103).

For both cultivators and sellers, Artificial intelligence (AI) can be incredibly helpful for meeting the changing needs of consumers over time (95-103). Artificial intelligence (AI) and IoT devices are helping professionals to track more information about product preferences, consumption habits, and more, so companies can proactively prepare their inventories accordingly (94-103). Artificial intelligence (AI) can also help companies to predict inventory levels based on current sales and supply. Instead of manually tracking inventory, sellers can use modern software to get instant notifications about low inventory and, if desired, automate supplier orders (94-103). This technology can also help sellers to identify products that are not moving quickly enough to be cost-efficient, so that they can remove those items from their inventory or raise their prices (94-95). For cultivators, Artificial intelligence (AI) -enhanced inventory management tools can also help to identify expansion opportunities (94-103). When sales start moving quickly enough, cultivators can use Artificial intelligence (AI) to weigh the potential profits and risks associated with scaling their growing operations (94-103).

In the increasingly crowded Cannabis industry, excellent customer service can make or break a business (94-103). Artificial intelligence (AI) can play a role in improving customer support by making it more efficient and less dependent on human labour (94-95). For example, growers and sellers can implement AI-powered product-matching tools that can help clients to identify the best products and dosages for their needs (94-95). Instead of requiring a consultation, even beginner Cannabis users can quickly determine what they need to purchase for the best experience possible (94-103). Other self-service opportunities can be vital to improving customer service, too (94-103). For example, when retailers implement a quality Artificial intelligence (AI) chatbot on their website, potential customers can get answers to common questions without reaching out over email or phone, which reduces wait times while helping these clients to get answers faster. This frees the customer service agents time for more complex support needs (94-103).

In general, moving into the future of the Cannabis industry, changes in demand should be a constant expectation. With Cannabis regulations growing more relax across the country and healthcare chatbots making prescriptions easier to obtain, demand can be expected to increase throughout the Cannabis supply chain (94-103). However, supply and demand fluctuations occur at different rates in different markets. Since the industry is relatively new in some areas and well-established in others, some markets may seen sudden surges in demand for certain types of products at different times (94-103). Modern Artificial intelligence (AI) technology can help companies mine data from social media mentions, website traffic, and more to generate actionable insights about the right products to produce and sell (94-103).

The increasing implementation of Artificial intelligence (AI) for sales and marketing is not exclusive to the Cannabis industry but can help to boost bottom line (94-100). With more predictive analytics and more accurate customer data, industries can generate campaigns that are more likely to work and develop sales pitches that are better tailored to specific audience members (94-95-1003). In the sales realm, artificial intelligence (AI) can help to identify the best sales opportunities leads who are likely to convert with a nudge, churned subscribers who could reactivate with a follow-up, and more (94-95, 103). In the marketing realm, Artificial intelligence (AI) technology is already helping many business leaders (including Cannabis business leaders) instantly to generate compelling content and save time (94-103). It can be programmed to help to create content that complies with the laws that Cannabis companies have to follow for example, by helping a customer to avoid restricted mediums or animations that could be attractive to minors (94-103).

With many Cannabis companies facing detrimental social media suspensions and ad deletions, new Artificial intelligence (AI) software is helping companies flag potential issues in their content, including hashtags, captions, and visuals that could initiate bans or shadow-bans on key marketing channels (94-103). While the future of the Cannabis industry could introduce more relaxed rules surrounding content marketing, especially if federal legalization occurs, age restrictions will continue to make Artificial intelligence (AI)-driven compliance essential (94-103).

IV. Application of Artificial Intelligence in Cannabis Plant Tissue culture

In 2021, the value of the global hemp market was estimated at around 4.13 billion US$, with an estimated 16.2% compound annual growth rate (CAGR) from 2021 to 2028 (14-100). However, the production still has not met the demand of the industry due to hindrance caused by the persistence of certain restrictions. There is a demand to increase the cultivated area along with the development of new elite cultivars with desired traits including higher production (14-100). The above-mentioned objectives can be achieved rapidly through classical breeding and the aid of modern biotechnological techniques like plant tissue culture (14-100). These techniques allowed the development of crops with superior qualities such as food, fuel, fiber, and feed (14-94-103). Investigation of *in vitro* regeneration protocols for Cannabis uncovered the recalcitrance nature of the hemp with low germination, regeneration, rooting, and acclimatization frequency (14-94-103). The combination of a low germination rate with the presence of contaminations hampers the establishment of an efficient and reproduciable *in vitro* regeneration protocol for hemp. Furthermore, dealing with germplasm available in the form of population makes its optimization exceedingly sensitive (14-94-103).

Application of different Machine learning (ML) and Feedforward networks, e.g. perceptrons, Single- and multilayered (MLP) algorithm modeling in the field of agriculture and plant biotechnology is a relatively new field used for predicting and optimizing variables in complex biological systems (14-103). In recent years, Artificial neural networks (ANNs) have been employed in plant tissue culture for the prediction and optimization of *in vitro* sterilization, germination, elicitation of secondary metabolites, somatic embryogenesis, and *in vitro* cell culture (14-103). Due to the important industrial implications of drug-type Cannabis, it is imperative to establish methods for the production of high quality biomass with consistent secondary metabolite profiles, which is achievable in part through micropropagation (14-103). Though micropropagation protocols showed promise to advance certain aspects of the Cannabis industry, there remain issues with conventional in vitro systems (14-103). Photosynthetically incompetent organs, and fragile roots are phenotypic traits commonly observed in cultures (14-103). Data collected were assessed using machine learning and evolutionary optimization algorithms to predict and optimize these factors for Cannabis maintenance and proliferation in vitro (14-94). Predictions were then tested in a validation experiment to identify the best optimization algorithm for in vitro plant applications (14-103).

In vitro micropropagation is a multi-factorial and complex biological process, because it is influenced by genotypes/cultivar and many keys interacting factors that would be required for optimizing this mentioned process (46-103, 105-207). Commonly, revealing all the information encrypted over the large datasets of biological interactions by traditional statistical techniques is a highly challenging task, particularly when datasets are nonlinear in nature, complex, noisy and ambiguous such as in multifactorial processes of *in vitro* culture (46-103). For this purpose, advanced computer-based technologies such as machine learning (ML) tools are capable to analyze and predict complex and multivariate datasets (14-103). Advantageously, the use of ML approaches provides the ability to learn autonomously and transform data into useful information without being humanly programmed (46-103).

Among the different algorithm-based ML tools, artificial neural networks (ANNs) have been proposed as the most powerful ML tools for modeling and predicting complex processes (46-94-100). Multilayer perceptron (MLP), generalized regression neural network (GRNN), and radial basis function (RBF) are three popular interpolation neural network models (46-103). MLP and other artificial neural networks (ANNs) are made up of a large number of neurons and each neuron has its weight (46-94). Indeed, the number of neurons in the hidden layers plays a significant role in the MLP's design (46-94). Although RBF and MLP have similar functions, RBF has a high ability to be used in more than one dimension, in contrast to the Multilayer perceptron (MLP) (46-94). RBF is claimed to be effective for predictions that use approximation multivariate functions wherever suitable characteristics are included (46-94-103). **Generalized Regression Neural Network** (GRNN) as another statistic artificial neural networks (ANNs) tool belongs to a category of RBF (46-94). Simplicity of network structure, very fast network training speed, strong non-linear mapping capability, ease of implementation, high fault tolerance, and high robustness in the solution of complex problems are excellent features of **Generalized Regression Neural Network** (GRNN) (14-103).

Recent studies have reported the good performance and superior predictive accuracy of artificial neural networks (ANNs) tools over traditional statistics for predicting and optimizing *in vitro* culture systems of different plant species such as chrysanthemum, passion fruit *Prunus* rootstock, tomato, chickpea, wheat, Cannabis, and ajowan (14-100). In addition, the combination of artificial neural networks (ANNs) with an evolutionary optimization algorithm as a superior and reliable computational method confers advantages to predict critical factors that impact plant growth parameters in *in vitro* culture systems (14-95). The non-dominated sorting genetic algorithm-II (NSGA-II), known as a search algorithm for optimizing multi-objective problems, is a powerful tool for solving various problems and optimizing and predicting complex processes easier (14-100). Also, it provides a simplistic interpretation of results, simultaneously (14-95). As an example, among applications of ML algorithms for *in vitro* seed germination in Cannabis, Hesami *et al*., employed and compared three models (i.e., MLP, GRNN, and RBF) in combination with the NSGA-II algorithm for predicting and optimizing the effect of culture media and carbon sources and concluded that GRNN-NSGA-II algorithm had good performance for this purpose (14-94-103).

In vitro seed germination is a complex biological process influenced by a variety of factors ranging from a medium condition such as type and concentration of macro/micronutrients and vitamins to the culture conditions such as temperature, and light (14, 40-94). Application of H_2O_2 treatment at different concentrations affected the germination, seedling emergence, and morphological traits of industrial Cannabis. Machine learning algorithms and MLP neural networks were utilized to predict the germination (14, 40-95). Another study was reported to optimize the concentration of H_2O_2 as a pre-sowing seed treatment to acquire maximum germination and morphological indices of hemp in MS (Murashige and Skoog Medium) media using Response surface methodology (RSM). Response surface methodology (RSM) is a highly efficient method for the optimization of the level (concentration) of factors (independent variables) in experimental studies like germination (40-95). The use of RSM for the estimation of predetermined inputs for germination has been documented to be effective for different crops like white sorghum, brown rice, mung bean, quinoa, and *Melia volkensii* (40-94). Furthermore, five different ML algorithms were employed for the prediction of the impact of different H_2O_2 concentrations on germination, seedling, and morphological traits of industrial cannabis (14, 40-90). The algorithms of Support Vector Classifier (SVC), Gaussian Process (GP), XGBoost, Random Forest (RF), and Multilayer Perceptron (MLP) neural network algorithm were utilized and trained the dataset for the prediction of output parameters (germination and growth indices) (14, 40-95). Application of H_2O_2 in plant tissue culture has been found to improve the sterilization, germination, and regeneration rate along with reduced contamination (14, 35-103).

Germination is a complex process and crucial for the growth and development of plants. The process of optimizing *in vitro* seed sterilization and germination is a complicated task since this process is influenced by interactions of many factors (e.g., genotype, disinfectants, pH of the media, temperature, light, immersion time) (14-95). One of the study investigated the role of various types and concentrations of disinfectants (i.e., NaOCl, $Ca(ClO)_2$, $HgCl_2$, H2O$_2$, NWCN-Fe, MWCNT) as well as immersion time in successful *in vitro* seed sterilization and germination of petunia (14-95). Also, the utility of three artificial neural networks (ANNs) (e.g., multilayer perceptron (MLP), radial basis function (RBF), and generalized regression neural network (GRNN)) as modeling tools were evaluated to analyze the effect of disinfectants and immersion time on *in vitro* seed sterilization and germination (14-95). Moreover, non-dominated sorting genetic algorithm-II (NSGA-II) was employed for optimizing the selected prediction model (14-95-103). The GRNN algorithm displayed superior predictive accuracy in comparison to MLP and RBF models (14-95). Also, the results showed that NSGA-II can be considered as a reliable multi-objective optimization algorithm for finding the optimal level of disinfectants and immersion time to simultaneously minimize contamination rate and maximize germination percentage. Generally, GRNN-NSGA-II as an up-to-date and reliable computational tool can be applied in future plant *in vitro* culture studies (14-95-103).

Micropropagation techniques offer opportunity to proliferate, maintain, and study dynamic plant responses in highly controlled environments without confounding external influences, forming the basis for many biotechnological applications (46-95, 103, 105-207). With medicinal and recreational interests for *Cannabis sativa* L. growing, research related to the optimization of in vitro practices is needed to improve the current methods while boosting understanding of the underlying physiological processes (46-95-103). Unfortunately, due to the exorbitantly large array of factors influencing tissue culture, existing approaches to optimize in vitro methods are tedious and time-consuming (14-103). Therefore, there is a great potential to use new computational methodologies for analyzing data to develop improved protocols more efficiently (14-103). Collected data were then assessed using multilayer perceptron (MLP), generalized regression neural network (GRNN), and adaptive neuro-fuzzy inference system (ANFIS) model and to predict in vitro Cannabis growth and development (14-103). Based on the results, **Generalized Regression Neural Network** (GRNN) had better performance than MLP or ANFIS and was consequently selected to link different optimization algorithms [genetic algorithm (GA), biogeography-based optimization (BBO), interior search algorithm (ISA), and symbiotic organisms search (SOS)] for prediction of optimal light levels (quality/intensity) and sucrose concentration for various applications (46-90). Predictions of in vitro conditions to refine growth responses were subsequently tested in a validation experiment and data showed that there was no significant differences between predicted optimized values and observed data (14-103). This study demonstrated the potential of machine learning and optimization algorithms to predict the most favourable light combinations and sucrose levels to elicit specific developmental responses (14-95). Based on these, recommendations of light and carbohydrate levels to promote specific developmental outcomes for in vitro Cannabis are suggested (14-103).

However, the selection of a proper model is dependent on various single or multiple inputs (factors) to predict the results more precisely (14-103). In plant tissue culture studies, optimization is highly desirable and the application of new computational approaches like machine learning algorithms using fewer inputs is on the rise in recent years (14-95, 103). Some of the commonly employed models include ML, MLP, radial basis function (RBF), and generalized regression neural network (GRNN) (14-103). However, the efficacy of each model may vary with the application of variable factors (inputs) and experimental setup (14-96-103).

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The machine learning assisted, multivariable micropropagation study has demonstrated that distinct growth responses in Cannabis can be shaped by changing the influences of sugar and light dynamics in the absence of PGRs (14, 40-95). The development of alternative protocols to guide plant growth toward specific responses showed endless value for numerous in vitro applications (14, 40-103). For instance, protocols to induce long stems, large internodes, many nodes, or many stems could be implemented when growing cultures for clonal propagation and sub-culturing, while cultures developing large root masses and large canopies could very well be more suited for ex vitro transfer (14, 40-103). In addition, culmination of the protocols devised could be implemented, perhaps to trigger different developmental responses during different growth phases (14-95). Finally, the results obtained from this experiment allowed to recommend GRNNSOS to be a more efficacious algorithm to study dynamic plant responses to multivariable stimuli in vitro for development of new methods, and optimization of current protocols (14-95). Rather than using traditional statistics to evaluate large datasets for making optimization predictions for tissue culture applications, the use of effective machine learning strategies for optimization of in vitro protocols should further be assessed as an alternative, or in combination with traditional statistical approaches to allow precision tissue culture practices (14-103).

V. Application of Artificial Neutral Networks (ANNs) in plant in vitro cultures

Artificial intelligence technology is currently the most promising and preferred method for modeling complex biological processes (14-103). **Artificial Neutral Networks (ANNs**) can also play a significant role as a prognostic tool with a high potential for modeling studies in plant in vitro cultures (14-103). ANNs imitate the construction of models of neural structures in the brain and copy the phenomena that occur in the human nervous system (14-103). The basic elements of ANNs are combined together and grouped in a layer of processing elements called **neurons** (14-103). The working of the neural network depends on the number of neurons, the neuron model and the network's architecture (14-103). An artificial neuron is composed of input parameters (weights associated with inputs and bias), the postsynaptic potential function, the transfer (activation) function and the output (14-103). The proper working of a network required a proper choice of parameter values, e.g. neuron weights and bias (14-60, 61-103). These ANN types are: i) Feedforward networks, e.g. perceptrons, Single- and multilayered (MLP); ii) Recurrence networks with feedback loops; iii) Self-organizing networks, such as Kohonen networks; iv) Radial basis function networks (RBFN); v) Resonance (ART – adaptive resonancetheory); vi) Probabilistic and hybrid (fuzzy and neurofuzzy logic) networks (14-90).

Machine learning as an evolving sub-branch of artificial intelligence (AI) has a great potential to solve a wide range of complex problems in biological systems (14-103). Indeed, ML aims to recognize the pattern within a given dataset and then developed a predictive model based on mathematical rules without specific step-by-step program given dataset and then develop a predictive model based on mathematical rules without specific step-by-step programming (14-103). In the plant tissue culture, different ML algorithms have been recently used for developing and optimizing in vitro propagation protocols in different species such as chrysanthemum, *Prunus* rootstock, Cannabis, Ajowan, wheat, wallflower, chickpea, tomato, and walnut (14-103). The reliability and accuracy of artificial neural networks (ANNs) as one of the most well-known ML have been approved in different in vitro culture studies (14-103). It has been shown that **Generalized Regression Neural Network (GRNN)** is one of the most powerful of ANNs has more accuracy than other ANNs in modeling and forecasting in vitro culture procedures (14-103). In addition to ML, optimization algorithms such as genetic algorithm (GA) can be used for the optimization of in vitro culture systems (14-103). Several studies have proposed a hybrid of GRNN and genetic algorithm (GA) as a powerful and reliable method for the prediction, modeling, and optimization of in vitro propagation protocols in different species (14-103)

The application of an Artificial neural networks (ANNs) also brings spectacular benefits due to the Artificial neural networks (ANNs) ability to capture nonlinear relationships between the data, regardless of their origin or type, and even among incomplete data sets, without the requirement that the user has prior knowledge regarding these data sets (14-103). Neural modeling can now be performed with a limited number of experiments, which consequently reduces the costs of plant tissue cultures grown under laboratory conditions and on an industrial scale (14-95). Finally, adding new inputs and outputs to the model database can easily increase the amount of knowledge derived through the use of Artificial Neutral Networks (ANNs) (14-103). This may provide a new outlook aimed at understanding the regulatory, developmental and physiological processes in plants (14-103). In the future, neural modeling could be used for the mechanization and automation of plant breeding via in vitro cultures and in the segregation of plant tissues in terms of quality, also in aseptic conditions (14-95). Moreover, Artificial Neutral Networks (ANNs) are very flexible and more useful than other strategies in hybrid models (14-103). Although artificial neural networks (ANNs) have shown significant progress in controlling bioprocesses, their use in the complex systems of plant tissue cultures is relatively infrequent (14-103).

Various factors such as type and concentrations of auxins and type of explant affect in vitro rooting of *P. caerulea*. Optimizing in vitro rooting can be considered as one of the most important steps to establish a whole plantlet propagation protocol (14-90). Recently, different ML algorithms have been widely implemented to predict and optimize plant tissue culture systems (14-103). In this study, **Generalized Regression Neural Network** (GRNN) was employed for the prediction and optimization of in

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vitro rooting of *P. caerulea* (14-95, 103). Based on experimental results, the developed **Generalized Regression Neural Network** (GRNN) model can accurately model and predict in vitro rooting of *P. caerulea* (14-90). In addition, these results demonstrated that GA was able to accurately find the optimized level of auxin and explant to maximize in vitro rooting of *P. caerulea* (14-94). The results of the this investigation showed that the hybrid of **Generalized Regression Neural Network** (GRNN) and genetic algorithm (GA) can open a helpful window for modeling and understanding in vitro propagation and can pave the way for further in vitro culture studies (e.g., direct and indirect organogenesis and somatic embryogenesis) in *P. caerulea* (14-95-103).

In vitro rooting as one of the most critical steps of micropropagation is affected by various extrinsic (e.g., medium composition, auxins) and intrinsic factors (e.g., species, explant) (14-90). In Passiflora species, in vitro adventitious rooting is a difficult, complex, and non-linear process. Since in vitro rooting is a multivariable complex biological process, efficient and reliable computational approaches such as machine learning (ML) are required to model, predict, and optimize this non-linear biological process (14-103). Therefore, in the current study, a hybrid of generalized regression neural network (GRNN) and genetic algorithm (GA) was employed to predict in vitro rooting responses (rooting percentage, number of roots, and root length) of *Passiflora caerulea* based on the optimization of the level of auxins (indole-3-acetic acid (IAA), indolebutyric acid (IBA), and 1-naphthaleneacetic acid (NAA)) and the type of explant (microshoots derived from leaf, node, and internode) (14-103). Based on the results, the GRNN model was accurate in predicting all in vitro rooting responses of *P. caerulea* (R2 > 0.92) in either training or testing sets (14-95). The result of the validation experiment also showed that there was a negligible difference between the predicted-optimized values and the validated results demonstrating the reliability of the developed GRNN-GA model (14-90). Generally, the results of the current study showed that **Generalized Regression Neural Network** (GRNN)-GA is a reliable and accurate model to predict and optimize in vitro rooting of *P. caerulea* (14-103).

Artificial neural networks (ANNs) are widely used in science and technology, and have been successfully applied in plant tissue cultures (14-103, 105-207). Furthermore, Artificial neural networks (ANNs) can simulate the growth of plants under different in vitro conditions (14-103). Their usefulness has been confirmed in the estimation of biomass in plant cell cultures and the length of shoots in vitro, in the classification of somatic embryos, evaluation of the physical conditions of an in vitro environment, and in the prediction of optimal conditions for in vitro culture to achieve maximum efficiency and productivity (14-103). Secondly, with the help of various types of neural models, in vitro -regenerated plants are sorted, respectively, to their quality and likeliness of further development (14-103). Thirdly, artificial neural networks (ANNs) are capable of predicting plant behaviour during in vitro rhizogenesis and subsequent acclimatization to ex vitro conditions (14-103). Several neural and neurofuzzy models for the aforementioned biological processes are reviewed (14-103). In addition, the fundamentals of neural modeling, namely the construction of ANNs, are presented and their flexibility and attractiveness are highlighted in many reviews (14-103).

Classification and pattern recognition models built by artificial neural networks (ANNs) are already being widely used in plant tissue cultures, usually because the selection of somatic embryos in embryogenic cultures is tedious, costly and time-consuming (14-95, 105-207). A system that recognizes the patterns and morphological features of carrot somatic embryos has been constructed using artificial intelligence technology (14-103). A hierarchical decision tree consisting of three layers and four nodes was used to obtain an optimal classification. Neural classifiers were incorporated into each node. Therefore, the pattern recognition system based on artificial neural networks (ANNs) has shown great potential for sorting embryos and artificial seed production automation (14-100). A system similar to the above classification has been applied to the somatic embryos of the Douglas fir (*Pseudotsuga menziesii*) (14-96, 103). The advantage of neural modeling over conventional tools has also been found during the calculation of the mass growth of plant cells (14-96, 103). A controlled microenvironment inside the culture vessels is a critical prerequisite for plant growth in tissue cultures. Environmental factors, such as CO_2 concentration, degree of ventilation, light intensity, and air temperature inside the culture vessels, affect the growth of regenerated plants (14-95, 103). In particular, an increase in air temperature at high light intensity inhibits growth. A finite element model (FEM) was constructed using artificial neural networks (ANNs) technology to predict the temperature distribution inside the culture vessels (14-95, 103). Honda et al. (1997) demonstrated a neural network assisted estimation of shoot length in in vitro regenerated rice (14-95). Data for calculations were taken from digitized images of regenerated cultures. Two different types of artificial neural networks (ANNs) with fuzzy logic (FNN – fuzzy neural network) were used for neural modeling to distinguish between the different regions of the shoot (14-95-103).

Micropropagation through the tissue culture technique is widely used for the propagation of plants (103, 105-207). The in vitro method used for growing plants is one of the most popular methods employed in plant biotechnology (105--207). Plant tissue culture is an in vitro aseptic culture of cells, tissues, organs or whole plant under controlled defined nutritional medium conditions often to produce the clones of plants (103, 105-207). The resulting clones are true to type of selected genotypes and used for the large scale plant multiplication (103, 105-207). Without in vitro techniques, plant micropropagation, androgenesis, gynogenesis, somatic embryogenesis, or the production of secondary metabolites would not be possible (103, 105-207). The main obstacle in the commercialization of micropropagation is the low survival rate of in vitro regenerated plants after transfer to ex vitro conditions

(14-103, 105-207). Although there are many biological processes that can easily be observed in plant tissue cultures, none of them are linear, and, moreover, they are influenced by many other factors as well (103, 105-207). Thus, appropriate modeling can be applied to quite accurately predict and simulate the growth kinetics of the plant cell cultures and also predict the resulting biomass (103). Environmental factors in vitro, such as differences in humidity and CO_2 concentration or the different distribution of light intensity and air temperature inside the culture vessel, have a particular impact on the quality of the regenerated plants during micropropagation, which resulted in a diversity of plants (14-57, 103, 105-207). The development of an automatic decision-making system that reflects the diversity of in vitro regenerated plants was much needed with regard to ensuring the high quality of micropropagation (14-95). An Artificial neural networks (ANNs) was built to assess the quality and to qualify sugarcane plants regenerated in tissue cultures. The artificial neural networks (ANNs) was based on photometric parameters which are true indicators for evaluating the behaviour of cultures capable of regeneration (14-90). The inputs to the artificial neural networks (ANNs) were a reflection of the leaf and the intensity of spectral brightness on digitized images (14-103).

Plant tissue culture experiments comprise a part of very complex studies (103, 105-207). The growth of plant tissues can be regulated and controlled by changing the composition of the culture media (14, 40-95-103, 105-207). Optimization of the mineral and plant growth regulator contents is very laborious and time-consuming. Therefore, predicting the composition of the growth media and the culture conditions is very useful for choosing the most favourable of these in order to achieve maximum productivity (14-90-103). Neural network software has been successfully used for modeling and optimization of the process of estimating the best in vitro culture conditions (14-103). Successful attempts at modeling in vitro culture parameters have also been made in the hairy root cultures of *Glycyrrhiza glabra*. This model consisted of an MLP performed in Matlab software (14-90).

Neural network software is used to simulate, research, develop and apply artificial neural networks (ANNs) (14-103). Generally, the software used for the design of ANNs: Statistica Neural Networks, Neural Networks Matlab Toolbox, INForm and FormRules (Intelligensys Ltd, UK), NeuroShell, Neuro- Solutions, Alyuda NeuroIntelligence, BioComp iModel, SPSS Neural Connection, etc. NeuroSolutions is also a powerful and flexible ANN modeling software package, which has an icon-based network design interface with advanced learning procedures and genetic optimization (see www. eurosolutions.com/products/ns) (14-103). Alyuda NeuroIntelligence supports all stages of artificial neural networks (ANNs) design and application (see www.alyuda.com) (14-100). BioCompModel is used in nonlinear predictive model development with self-optimizing (see www.biocompsystems.com/products/ imodel) (14-103). SPSS Neural Connection is a powerful combination of ANNs and traditional statistical methods and can be used for classification, prediction, time-series forecasting and clustering (14-103). Artificial neural networks (ANNs) are, therefore, increasingly used for the interpretation and analysis of data obtained in studies conducted on tissue cultures (14-103).

VI. Conclusion

Cannabis (*Cannabis sativa* L.) is a complex, polymorphic plant species, which produces a vast array of bioactive metabolites, the two major chemical groups being cannabinoids and terpenoids. The psychoactive cannabinoid, Λ9-Tetrahydrocannabinol (Λ9-THC) and the non-psychoactive Cannabidiol (CBD), are the two major Cannabinoids that have monopolized the research interest. Currently, more than 750 Cannabis hybrid varieties are commercially available, providing access to a multitude of potent extracts with complex compositions, whose genetics are largely inconclusive. Recently introduced legislation on Cannabis cultivation in many countries represents a great opportunity, but at the same time, a great challenge for Cannabis research and development (R&D) toward applications in the pharmaceutical, food, cosmetics, and agrochemical industries. Therefore, artificial intelligence (AI) has been applied in order to solve many problems of Cannabis industries from cultivation to the product management. Artificial intelligence (AI) is a powerful tool that can be applied in all aspects of the Cannabis industry.

Artificial intelligence (AI) is applied to make computers smart and intelligent by giving them the ability to think and learn using computer programs or machines, i.e., that can think and function in the same way that people do. From a philosophical perspective, Artificial intelligence (AI) has the potential to help people live more meaningful lives without having to work as hard, as well as to manage the massive network of interconnected individuals, businesses, states, and nations in a way that benefits everyone. Thus, the primary goal of Artificial intelligence (AI) is to enable computers and machines to perform cognitive functions such as problem-solving, decision making, perception, and comprehension of human communication. Therefore, AI-based modeling is the key to building automated, intelligent and smart systems according to today's needs. This has emerged as the next major technological milestone, influencing the future of practically every business by making every process better, faster, and more precise.

Plant tissue culture experiments comprise a part of very complex studies. Due to the important industrial implications of drug-type Cannabis, it is imperative to establish methods for the production of high quality biomass with consistent secondary metabolite profiles, which is achievable in part through micropropagation. The growth of plant tissues can be regulated and controlled by changing the composition of the culture media. Optimization of the mineral and plant growth regulator contents is very laborious and time-consuming. Artificial neural networks (ANNs) are widely used in science and technology, and have been successfully applied in plant tissue cultures. Therefore, predicting the composition of the growth media and the culture conditions is very useful for choosing the most favourable of these in order to achieve maximum productivity. Neural network software has been successfully used for modeling and optimization of the process of estimating the best in vitro culture conditions. It has been shown that **Generalized Regression Neural Network (GRNN)** is one of the most powerful of artificial neural networks (ANNs) has more accuracy than other artificial neural networks (ANNs) in modeling and forecasting in vitro culture procedures.

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