ENNOV WHITE PAPER

AI and Its Impact on Life Sciences

The age of Artificial Intelligence has begun and it's here to stay. Discover how Generative AI is revolutionizing drug development, healthcare, and regulatory compliance, shaping the future of the industry.

Software for Life

www.ennov.com | contact-us@ennov.com | +1 (833) 366-6887

Table of Contents

The Executive Summary

This document provides a comprehensive analysis of Artificial Intelligence (AI) and its significant impact on the life sciences sector. It begins with a historical overview, tracing the development of AI from early neural networks to today's sophisticated machine learning and natural language processing technologies.

This paper primarily concentrates on Generative AI, a notable branch of AI distinguished by its capability to create diverse content including text, images, and intricate data interpretations from minimal user input. We conduct a comprehensive exploration of Generative AI, examining its evolution, current state, and future prospects. This includes an assessment of its extensive potential as well as the challenges it encounters.

AI has practical applications across various industries, particularly its transformative effects in healthcare and life sciences. The paper demonstrates how AI is revolutionizing personalized medicine and enhancing pharmacovigilance through literature monitoring, underscoring its diverse and comprehensive applications. We present real-world examples that show AI's role in improving efficiency and driving innovation in these essential sectors.

Designed to serve as both an informative resource and a strategic guide, this document assists professionals in navigating the evolving AI landscape within the life sciences field. It reflects our commitment to staying at the forefront of technological advancements, ensuring our clients and partners can fully leverage AI's capabilities.

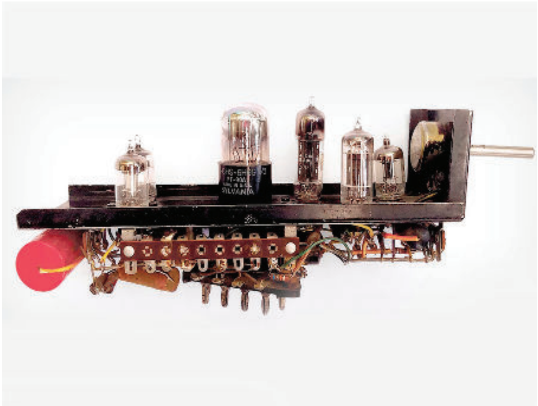
At Ennov, we are confident in AI's ability to reshape the future of life sciences. Through this white paper, we invite you to join us in exploring and contributing to this exciting era of discovery and innovation.

AI's Slow Coming of Age

Early Neural Networks

The inception of neural networks can be traced back to 1951, marked by the creation of a device using 3,000 vacuum tubes to simulate 40 neurons. This was followed by the development of the Perceptron in 1955, the first artificial neural network (ANN) with learning capabilities, and in 1969, the introduction of the backpropagation algorithm, enabling multi-layer neural networks to learn.

The 1980s saw significant advancements with the introduction of Convolutional Neural Networks (CNNs), enhancing image recognition, and Recurrent Neural Networks (RNNs), improving handwriting and speech recognition capabilities. However, limitations in computational power and a lack of understanding regarding the limitations of gradient learning in multilayer neural networks meant that deep learning's potential could not be fully explored until the 2000s.



1951 - The first artificial neural network called SNARC

Symbolic AI

The domain of symbolic AI saw its first major achievement with the development of a checkers-playing program in 1952, also notable for being the first learning-capable program. The invention of the LISP programming language in 1958 simplified the creation of symbolic AI systems. By 1965, the development of the first Expert System introduced formal reasoning capabilities using Boolean rules and inference, though by the 1980s, the limitations of expert systems in addressing real-world problems became apparent, contributing to the onset of the so-called "AI Winter."

Symbolic Computation

Symbolic computation, or computer algebra, involves the representation and automatic manipulation of mathematical expressions to solve problems. Although initial implementations began in the 1960s, it took decades for this approach to mature into the powerful tool it is today. Currently, the integration of generative AI with symbolic computation represents a promising research direction.

Probabilistic and Fuzzy AI

The introduction of Fuzzy Logic in 1973 facilitated the modeling of partially true concepts and the mimicry of human reasoning on imprecise notions. The development of pattern recognition and fuzzy systems in the following decades allowed for the incorporation of human expertise into a wide array of systems, from simple to complex.

The foundation for probabilistic reasoning was laid in 1763 by Thomas Bayes, whose theorem supports reasoning based on the probabilities of events. This theoretical groundwork led to the development of Bayesian Networks in 1988, significantly enhancing the capability to model uncertainty and informed decision-making in AI systems.

The Rise of Machine Learning

In the 1980s and 1990s, machine learning heralded a significant shift in AI, leading to the development of diverse methodologies that underpin the three primary types of machine learning recognized today:

- **Supervised learning** uses a training dataset with predefined outputs to guide the learning process.
- **Unsupervised learning** identifies patterns in data without predefined outputs, revealing the data's inherent structure.
- **Reinforcement learning** operates through periodic feedback, adjusting the system's outputs based on their accuracy.

This period saw the creation of various learning methods, including regression methods (focusing on statistical relationships), stochastic gradient descent (notably backpropagation for ANNs), and similarity-based approaches like K-nearest neighbors. Additionally, ensemble learning emerged, enhancing predictions by really integrating multiple models, alongside probabilistic and heuristic learning (such as Bayesian methods, Gaussian processes, Markov models, Monte Carlo simulations, simulated annealing, and genetic algorithms). Dimensionality reduction and feature engineering techniques were developed to simplify complex problems by altering the representation of data in the vector space, making it easier to analyze.

Advancements in Natural Language Processing (NLP)

Over the years, NLP has evolved significantly, leveraging advances in AI and machine learning:

- NLP was invented in the 1960s. It was rule-based and could only handle specific types of inputs
- The 1980s introduced Generative Grammar, facilitating complex NLP tasks like language translation through formal syntax and grammar analysis.
- By the 1990s and 2000s, statistical machine learning approaches, such as Conditional Random Fields (CRF), advanced text parsing, speech recognition, and translation capabilities.
- The late 2010s saw the advent of Large Language Models (LLMs), which significantly enhanced general-purpose NLP performance across various tasks.

Today, "traditional" NLP algorithms and LLMs are both used. Each approach has its specific strengths:

- Traditional NLP is very cost efficient at executing many specific natural language tasks. This type of algorithm can be executed on standard hardware and easily deployed.
- LLMs are better at many tasks, especially when text generation is involved. They nevertheless generally require deployment on dedicated GPUs or TPUs and are therefore more costly and complex to deploy.

The First AI Surge

The 2000s and 2010s have seen a quantum leap in AI's capabilities, driven by key factors:

- **Technological Breakthroughs:** The advent of AI-dedicated GPUs and TPUs significantly boosted the computational power for training neural networks, facilitating the processing of extensive datasets.
- **Data Revolution:** The digital age has produced an abundance of data, crucial for training and refining AI models.
- **Deep Learning Advancements:** Innovations in neural network designs, especially the introduction of LSTM (long short-term memory) algorithms by Sepp Hochreiter in 1997, overcame previous limitations of backpropagation in multi-layer networks. This enabled "deep" learning through networks with many neuron layers, each extracting progressively higher-level data features.

The evolution of efficient deep learning techniques and neural networks became the most significant and rapidly industrialized AI segment during this period. Large neural networks offered strategic advantages to major corporations, especially tech giants, enabling the widespread deployment of sophisticated pattern recognition and automatic translation services.

AI EVOLUTION TIMELINE

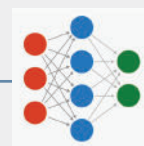
1951 — First Neural network invented by Marvin Minsky & Dean Edmunds

1957 — Noam Chomsky's book "Syntactic Structures" introduces Generative Grammar

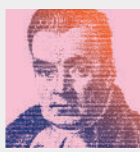
1965 — First Expert System developed by Edward Feigenbaum et al.

1970 — The backpropagation algorithm invented by Seppo Linnainmaa enables deep learning of Neural Networks

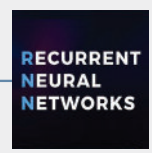
1973 — Lotfi Zadeh invents Fuzzy Logic, enabling to reason on unprecise notions



1982 — John Hopfield's Recurrent Neural Network improves speech recognition and language processing

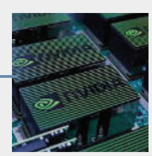


1988 — Bayesian Networks invented by Judea Pearl enable to do probabilistic reasoning

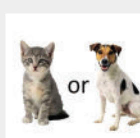


1997 — The LSTM (long short-term memory) algorithm of Sepp Hochreiter enables "very deep learning" of Neural Networks

2001 — Conditional Random Fields (CRFs) by Lafferty et al. enable advances in text parsing, speech recognition and translation

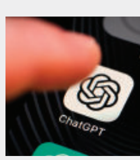


2009 — Nvidia increases deep learning speed by 100 times with GPUs for deep learning



2010s — Mass scale industrial applications of deep learning for speech and image recognition

2017 — The modern Transformer algorithm is introduced by Ashish Vaswani et al., starting the LLM revolution



2022 — OpenAI first releases ChatGPT on November 2022, triggering a mass adoption of generative AI

Generative AI: The Breakthrough That Changes Everything

Generative AI represents a monumental leap forward in artificial intelligence, characterized by neural networks known as Large Language Models (LLMs) that are adept at producing a diverse range of content, including text, images, code, and videos, in response to user-provided text prompts.

Historically, techniques such as genetic algorithms and L-systems were employed in the 1980s and 1990s to generate content inspired by natural processes. However, the advent of modern LLMs has ushered in an era where content can be generated through advanced neural network architectures based on simple user prompts:

- **Mixture of Experts (MoE):** Introduced in 1991, this architecture utilizes multiple models in tandem. In 2024, it underpins promising LLMs like Mixtral, showcasing its enduring relevance and utility.
- **Diffusion Algorithms:** Since their introduction in 2015, these algorithms have revolutionized image generation, iteratively applying noise and denoising techniques until the desired image emerges.
- **The Transformer Algorithm:** Proposed in 2017, this has become the cornerstone of contemporary LLMs used for generating text or code, exemplified by OpenAI's GPT, Meta's LLaMa, and Google's Gemini (previously Bard). It's core mechanism, the Attention Mechanism, enables the neural network to contextualize words effectively, predicting subsequent tokens with remarkable accuracy.

Simple as it may seem, this generic approach has proved to deliver "Emerging Capabilities" every time the network is scaled (adding more neurons and layers). For example, much to the surprise of early users, Transformer-based LLMs proved to be able to translate texts from one language to another once scaled, although they were never meant to originally.

These emerging capabilities are numerous, making LLMs extremely flexible. While "traditional NLP" requires the use of multiple algorithms that must be tuned by experts to achieve a specific goal, generative AI has completely changed the game by providing a universal approach that can achieve countless goals, according to its user's need.

Other factors make this universal capability extremely useful in practice:

- **Ease of Use:** LLMs simplify interaction, requiring only detailed text prompts from users to deliver results. No longer are "PhDs in AI" required to successfully use AI. This leads to mass adoption of the technology and completely changes AI from an elitist technology to a grassroots movement – everybody in the company is now a potential user capable of crafting an LLM to suit his or her particular need.
- **Versatility in Content Creation:** Addressing a common need, LLMs offer flexible solutions for generating a wide array of content types, from code and documents to images and summaries.
- **Comprehensive Capabilities:** LLMs excel in extracting information, generating diverse texts, answering questions, summarizing, translating, enhancing text relevance, emotional analysis, error detection, conversation, logical reasoning, and integrating various data types for comprehensive analyses.
- **Adaptability and Customization:** Through techniques ranging from Retrieval Augmented Generation (RAG) to Neural Network Model Fine-Tuning, LLMs can be tailored to specific domain knowledge, enhancing their utility in specialized fields.
- **Multimodality:** Evolving beyond text, modern LLMs interpret and generate multifaceted outputs including charts, graphics, and tables, broadening their applicability.
- **Extendibility and Integration:** Advanced LLMs can identify their limitations and delegate specific tasks to specialized applications via APIs, effectively becoming central orchestrators of a wide range of applications.

Despite its transformative potential, generative AI faces inherent limitations. Yet, these constraints do not signal an imminent "AI Winter"; instead, they highlight areas for ongoing innovation and adaptation. Here's why these limitations are unlikely to derail the progress of generative AI:

LIMITATION	MITIGATION
Limited Creativity: Transformer Models' creativity is constrained by the data they were trained on and their training principle which is to predict the most probable words that will complete an existing text. They are "advanced parrots" rather than true creators.	We do not need LLMs to be AGIs (Artificial General Intelligence that could learn to accomplish any intellectual task that human beings can perform) for them to be immensely useful. There are so many tasks that we can automate or improve and that do not require a very high level of creativity.
Data Dependence: LLMs rely on the data they were exposed to during training. If the training data is biased or incomplete, the generated output may reflect those limitations.	This is why enterprises in various industries are learning how to create their own LLMs or fine-tune general-purpose LLMs. There will likely not be a "One LLM to rule them all" but rather Multiple LLMs dedicated to specific industries.
Ethical Concerns: Generative AI can inadvertently produce harmful, offensive, or biased content. Ensuring ethical guidelines during training and deployment is crucial.	Modern LLMs such as ChatGPT include a phase of fine-tuning of their algorithm (based on reinforcement learning), where humans qualify the quality of the responses that the LLM provides. Meeting ethical guidelines is indeed included from the start in their design.
Computational Demands: Training and running generative models are computationally intensive. Large-scale models require substantial resources, limiting accessibility for everyone.	GPUs and TPUs are progressing very fast to alleviate that constraint. Besides, some approaches such as the Mixture of Experts enable to create LLMs that are ten times smaller while retaining the same capabilities as larger models.
Lack of Explanation: Understanding why a generative model makes specific decisions can be challenging. Interpretability remains an ongoing research area.	LLMs can provide explanations about their decisions when they are asked to do so. They are also capable of reasoning step by step when prompted to do so, which also provides intermediary results along their decision process.
Over-Reliance: Dependence on a few large proprietary LLMs is a concern as the largest LLMs are built by a few technology companies that can afford the vast resources required to train them.	Open-source LLMs are progressing very fast and trail proprietary LLMs by about a year only. With open-source LLMs and proprietary ones, companies can fine-tune these models on their own data and build a specific version for their own use.
Overfitting: Similar to other machine learning models, generative AI is prone to overfitting, meaning it may perform well on its training data but poorly on unseen data. This overfitting can lead to two significant issues: the inadvertent exposure of confidential information contained within the training data and the emergence of novel security threats that are challenging to mitigate.	Avoiding security risks is essential for companies, which is why they are advised not to exchange confidential information with "public" LLMs, but rather deploy their own LMM instances. The study of the new types of attacks made possible with LLMs is a booming domain – we believe that over time security best practices will emerge to alleviate that risk.
Uncertainty Handling: Generative models struggle with quantifying uncertainty. They often produce confident but incorrect outputs.	LLMs generally have a parameter that users can set that makes the LLM either more precise or more creative but also likely to produce incorrect results. Another approach that works well is to ask the LLM to verify that the answer that it has just provided is correct. Managing uncertainty is certainly a challenge but can be done with the right approach.

Given these considerations, it's evident that generative AI is poised to significantly transform various industries. Businesses that delay in adopting its capabilities may soon find themselves at a competitive disadvantage. This technological advancement is also likely to induce shifts within the workforce and employment landscapes, favoring those who adapt to and integrate new AI technologies into their skill sets and operational strategies.

Generative AI Is a Game Changer

	NLP+MACHINE LEARNING	GENERATIVE AI (LLMS)
PURPOSE	Multiple models & algorithms that are each good at a specific thing	Universal model: can be used to do multiple things Emerging capabilities are discovered every time LLMs are scaled Multimodal: handles text, image, video…
CONFIGURE	PhD required to configure the algorithms optimally	Writing a prompt can be learned by anyone
PROGRESS	Relatively mature algorithms that have been developed in the 80s, 90s, 2000s…	Fast-moving technology: new algorithms + NVIDIA plans to multiply by 1000 the power of its AI chips in 5 years
CAPABILITY	Generating content is extremely difficult (better at recognition, extraction, classification)	Generating content is very easy (summarizing, translating, creating new content…)

Implications for Every Industry

The vast amounts of unstructured data—documents and information—present in enterprises are set to become a key asset for generating business value, thanks to Large Language Models (LLMs). Unlike earlier AI initiatives that demanded extensive structured data, often at high collection costs, generative AI can unlock many practical applications across all sectors.

Examples include:

- Assisting programmers in writing, proofreading, and translating code between languages.
- Streamlining the production of detailed texts, charts, graphics, and reports that traditionally require considerable effort.
- Enhancing risk detection by analyzing varied information types.
- Facilitating predictions based on comprehensive data sets.
- Automating the generation of structured documents like contracts, orders, and invoices.
- Extracting relevant information from diverse document types, regardless of their format.
- Improving customer support and assistance through the use of historical cases and knowledge bases.
- Personalizing interactions with clients on a large scale.
- Analyzing extensive unstructured data sets to uncover valuable insights.

Industries must proactively explore and test how generative AI can be applied to foster productivity improvements, cost reductions, or novel client engagement methods.

Moreover, the long-term impact of generative AI is likely to bring about significant disruption across various sectors. Innovative business models that were previously unfeasible are beginning to emerge, as seen in niches like stock image photography. In this domain, images are increasingly generated by AI based on prompts, reducing costs and reliance on traditional photography. This trend towards AI-generated content is expanding, with users becoming adept at creating custom images for their needs. Companies facing the highest risk of disruption by these shifts should urgently devise contingency plans to address the forthcoming challenges and opportunities.

AI TECHNOLOGY LANDSCAPE

Implications for Healthcare and Life Sciences

At Ennov, we of course experiment using new AI technologies internally to improve how we work (for example how AI can help us improve product development or customer support).

But we are even more involved in how we can help our Healthcare and Life Science clients apply AI to make their business more efficient and agile. Generative AI has opened a new frontier in healthcare and life sciences, with many potential applications.

Transformative Impact on Healthcare

AI's potential for healthcare is truly transformative, as it addresses three critical challenges that healthcare faces today:

1. **Addressing Physician Shortages:** AI has the potential to mitigate the shortage of trained medical professionals, a pressing issue in both aging societies with a growing patient base and developing regions lacking sufficient healthcare workers and training facilities. AI can offer support through:
   - **AI-Assisted Diagnostics and Prescriptions:** Technologies such as AI-assisted diagnostic imaging in radiology can significantly reduce radiologists' workloads and decrease error rates. Moreover, AI's applications span across various specialties including dermatology, ophthalmology, and pathology, with algorithms already outperforming humans in detecting conditions like skin cancer and diabetic retinopathy.
   - **AI-Based Diagnostics and Prescriptions:** In locations where medical professionals are scarce, AI can provide essential diagnostic and prescription services, bridging the gap in healthcare access.

2. **Enhancing Healthcare Quality:** AI contributes to healthcare quality improvements in several ways:
   - **Reliable Diagnostics:** AI's precision in diagnostics, whether assisted or fully automated, enhances the accuracy of patient assessments.
   - **Personalized Treatments:** By analyzing comprehensive patient data—including environmental, lifestyle, genomic, and real-world information—AI enables tailored treatment plans. Technologies like RNNs and LSTMs are instrumental in parsing complex sequence data from genomics and patient records.
   - **Risk Assessment:** AI tools can identify patients at high risk for conditions like cancer early on, recommending preventative measures or screenings accordingly.

3. **Controlling Healthcare Costs:** AI can help manage escalating healthcare expenses through:
   - **Operational Efficiency:** Automating administrative duties and optimizing resource distribution, such as bed allocation and staff scheduling, can alleviate the administrative load on healthcare professionals.
   - **Telemedicine Advancements:** AI enhances telemedicine by enabling intelligent monitoring for patients with chronic conditions, reducing the need for in-person visits.
   - **Empowering Patients:** AI-powered health applications allow individuals to conduct self-assessments and gain insights into preventive care, fostering a proactive health management approach and potentially reducing healthcare costs.

While this overview is not exhaustive, it underscores the significant promise of generative AI in healthcare, both now and in the future. The technology's capacity to improve access, quality, and affordability in healthcare positions it as a pivotal tool in transforming the industry.

Use Cases

USE CASE 1	USE CASE 2
Personalized medicine: A 45-year-old woman is diagnosed with TNBC, a type of breast cancer usually aggressive and hard to treat. Taking into account that she has a mutation in the BRCA gene which increases breast cancer risk, her high level of immune cells in the tumor, her history of benign breast disease, and her history of hypertension and diabetes, an AI system proposes a personalized treatment plan as well as lifestyle recommendations that will improve her chances of curing her cancer, prevent recurrence and ensure less side effects from the therapy.	**Literature monitoring for pharmacovigilance:** Using a generative AI-enabled software, a mid-size pharmaceutical company regularly scans the scientific literature to find occurrences of the use of its drugs or of the same active ingredients that would require the creation of pharmacovigilance adverse event cases. The AI automatically scans thousands of new papers each week, surfaces the ones that are relevant, checks whether the case already exists, prepopulates metadata concerning the proposed case, estimates the likelihood of causal relationship as well as the severity of the case.
› **Step 1:** AI proposes a personalized treatment plan	› **Step 1:** Relevant scientific papers are identified
› **Step 2:** Treatment plan can be adjusted if needed	› **Step 2:** Causality and severity are estimated
› **Step 3:** Lifestyle changes reduce risk of recurrence	› **Step 3:** Case pre-populated with data & summary

Broad Impact for Life Sciences

AI and especially generative AI also has broad impacts for Life Sciences, spanning the whole spectrum of the drug development life cycle.

It can accelerate drug discovery by improving drug target identification through biological and medical data analysis, accelerating drug screening by high-throughput screening of vast compound libraries for promising drug candidates, and enabling predictive modeling of the efficacy and safety of compounds, reducing the need for extensive laboratory tests.

AI can also help optimize the design and management of clinical trials in various ways:

- Accelerate patient recruitment by analyzing large datasets to identify suitable trial participants.
- Optimize protocol design by analyzing past trials and outcomes, leading to more effective and efficient trials.
- Accelerate clinical study setup by accelerating the process of turning a study protocol into a workable EDC and eCRF.
- Continuously monitor and analyze trial data to identify trends and anomalies, or predict potential outcomes, ensuring better trial safety and data quality.
- Automate tedious tasks throughout the clinical trial process, for example in building an eTMF or generating study reports or clinical study narratives.

The potential impact of AI on regulatory affairs is also sizable. This includes for example saving time on tedious, repetitive processes, facilitating the creation of regulatory documents, helping assess the impact of regulatory changes:

- Data extraction techniques from existing texts such as narratives, notes and existing documents can facilitate the filling of the numerous metadata that are required to fill the forms used in many regulatory processes such as RIM/IDMP data entry for example.
- AI can facilitate regulatory intelligence by analyzing regulatory guidelines and documents submitted by competing vendors to authorities.

AI can be used in pharmacovigilance and drug safety to accelerate case entry, data quality and signal detection:

- Data extraction from narratives can accelerate the tedious process of filling case entry forms or automatically check if data from narratives match data filled in case entry forms.
- AI can accelerate literature monitoring and make it more reliable as well, by automatically identifying scientific papers worth being examined and extracting the key information necessary to fill the case if needed.
- Finally, generative AI can be used to improve signal detection, especially in cases when data are sparse and statistical approaches difficult to apply.

In Medical Affairs, LLMs can facilitate the creation of many types of documents including:

- Regulatory Medical Writing: safety updates (automated literature review or safety reports drafting), clinical study reports (background, methods sections drafting).
- Scientific Communications: helping draft research papers, abstracts or posters
- Marketing Support: product monographs (drafting initial content or summarizing literature and evidence).
- Medical Information Responses: automatically create FAQs or SRLs from product monograph, clinical trial data, and safety updates.

Quality management is another domain where AI's potential is sizable, for example for improving decision-making in QMS systems to enhance quality and improve compliance or enabling time savings in user training management for example.

Post-marketing activities are also areas where productivity gains can also be achieved by improving the management and the efficiency of marketing campaigns, as well as improving the productivity of time-intensive event management and transparency-related activities.

Overall, AI can help make the whole drug lifecycle shorter and less time-intensive, improving costs and accelerating the drug's time to market.

Where Ennov Stands

Ennov recognizes the significant value that both "traditional" NLP/machine learning and the more recent advancements in generative AI bring to regulated content management within the Life Sciences sector.

To harness these technologies, we have incorporated a comprehensive AI module into our platform, which includes both traditional NLP and machine learning functionalities, alongside generative AI capabilities.

This inclusive module is designed to bolster Ennov's offerings on both a general and specific application basis:

- It enables advanced features such as intelligent NLP-based search and automated dashboard generation across all Ennov applications.
- It introduces new functionalities within each of Ennov's primary areas of focus: regulatory affairs, pharmacovigilance, quality management, clinical studies, and event management.

As AI technology continues to advance, Ennov is committed to ongoing enhancement of these features. Our goal is to ensure that healthcare and life science organizations utilizing the Ennov platform will consistently benefit from the cutting-edge developments in AI, particularly generative AI, to drive significant progress in their operations.

> More than 300 Life Sciences companies around the world are powered by **Ennov**

Glossary

Artificial Neural Network (ANN): A computational model inspired by the human brain's network of neurons, capable of learning and making predictions or decisions.

Backpropagation: An algorithm for training neural networks, involving the adjustment of weights in the network based on the error rate obtained in the previous epoch (iteration).

Bayesian Networks: A probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG).

Convolutional Neural Network (CNN): A class of deep neural networks, most commonly applied to analyzing visual imagery, characterized by their convolutional layers that automatically and adaptively learn spatial hierarchies of features from input images.

Directed Acyclic Graph (DAG): A conceptual representation of a series of activities, or, in other words, a mathematical abstraction of a data pipeline

Deep Learning: A subset of machine learning involving neural networks with many layers, enabling the modeling of complex patterns and predictions.

Expert System: A computer system that emulates the decision-making ability of a human expert, using predefined rules and knowledge.

Fuzzy Logic: A form of many-valued logic that deals with approximate, rather than fixed and exact reasoning, mimicking the way humans make decisions.

Generative AI: AI systems capable of generating new content, including text, images, and videos, based on the data they have been trained on.

Large Language Models (LLMs): A type of generative AI model that processes and generates human-like text based on the input it receives.

Long Short-Term Memory (LSTM): A special kind of recurrent neural network (RNN) capable of learning long-term dependencies, particularly useful in sequence prediction problems.

Machine Learning: A subset of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

Mixture of Experts (MoE): An ensemble machine learning approach where multiple models (experts) are trained to solve the same problem and then combined in a way that leverages their strengths.

Natural Language Processing (NLP): The ability of a computer program to understand human language as it is spoken and written, referred to as natural language.

Perceptron: The simplest type of artificial neural network, used in supervised learning for binary classifiers.

Retrieval-Augmented Generation (RAG): The process of optimizing the output of a large language model.

Recurrent Neural Network (RNN): A class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence, allowing it to exhibit temporal dynamic behavior.

Regression Methods: Statistical methods that allow for the modeling and analysis of relationships between variables.

Reinforcement Learning: A type of machine learning where an agent learns to behave in an environment by performing actions and seeing the results.

Stochastic Gradient Descent: A method to find the minimum of a function by moving in the direction of the steepest decrease as defined by the gradient.

Symbolic AI: An area of AI research that focuses on the manipulation of high-level, human-readable symbols, contrasting with approaches that work directly with raw data.

Transformer Algorithm: A model architecture used primarily in the field of natural language processing (NLP) that relies on an attention mechanism to boost the speed and effectiveness of learning.

Unsupervised Learning: A type of machine learning that looks for previously undetected patterns in a dataset without pre-existing labels.

Software for Life

About Ennov

Ennov offers a unified compliance platform to power solutions that span all regulated business areas (Regulatory, Quality, PV, Clinical, Commercial). From leading pharmaceutical companies to start-up biotechs, we proudly serve over 300 companies and 300,000 users worldwide.

For more than 20 years, we have been developing innovative, powerful and easy-to-use software for regulated content, data and process management. Our solutions are designed and built to support the entire Life Sciences R&D continuum. Ennov is ISO 9001:2015 certified for all software products and processes and we boast a 100% success rate in customer audits.

Raleigh

223 S West St., Ste 1000
Raleigh, NC 27603, USA

+1 (833) 366-6887

Paris

149 avenue de France
75013 Paris, France

+33 (0)1 40 38 81 38

Cambridge

5 Eaton Court Road,
Colmworth Business Park
Eaton Socon, St Neots
Cambridgeshire PE19 8ER, UK

+ 44 1 480 21 22 23

Japan

CCI France Japon Nihonbashi
Honcho YS Building, 2F
2-2-2 Nihonbashi Honcho,
Chuo-ku
Tokyo 103-0023, Japan

+81-3-4500-6670

www.ennov.com | contact-us@ennov.com | +1 (833) 366-6887