

THE PENROSE



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Welcome to the Competition Issue of Penrose Magazine!

Penrose is a STEM magazine where we hope to establish a community of young people who are passionate about STEM and want to further their knowledge beyond the curriculum. This installment features the winning articles from the Penrose Magazine Winter 25-26 Competition revolving around the theme 'Intersections of AI.'

Note: Each article is displayed as it was submitted. The only changes that may have been made by the Penrose Magazine team were to citations to meet our formatting standards.

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The Cure in the Algorithm: How Explainable Deep Learning Is Reshaping Antibiotics

The Horizon of The AMR

In the current medical landscape, it is feasible to envision a future where a simple wound or minor infection could mean a death sentence. Deaths caused by AMR (Antimicrobial Resistance) worldwide are trending towards a 13.4% increase between 2022 and 2030, which translates to a rise to 1.28 million annual deaths [1].

By 2025, a critical period has already begun, where direct deaths from AMR will exceed 1.14 million annually. Furthermore, it is estimated that more than 39 million people will die directly from AMR, and 169 million deaths will be associated with AMR between 2025 and 2050 [1].

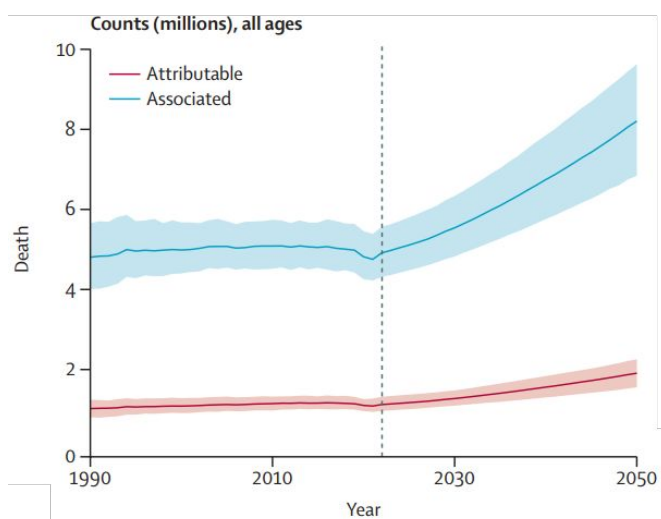


Fig. 1. Global attributable and associated AMR burden [1].

Despite the growing urgency of antimicrobial resistance, the stagnation in the discovery of new antibiotics has been driven by multiple factors. One major limitation is the repeated rediscovery of already known molecules, a phenomenon

known as dereplication, which slows antibiotic discovery by diverting time and resources towards compounds that lack therapeutic advantage. In addition, the difficulty of generating next-generation antibiotics through the modification of complex molecular scaffolds has further constrained the antibiotic development pipeline. Together these limitations have contributed significantly to the global AMR crisis [2].

Historically, antibiotics were discovered primarily by analyzing soil microbes in search of secondary metabolites that inhibited the growth of pathogenic bacteria [2]. However, a major breakthrough was achieved with the development of an artificial intelligence algorithm at MIT that managed to identify “Halicin”, a compound originally investigated and later discarded as a treatment for diabetes. This compound was shown to be a broad-spectrum antibiotic capable of killing extremely resistant bacteria [2].

This artificial intelligence-driven drug discovery approach enables the exploration of large and chemically diverse compound spaces beyond traditional similarity-based screening, reducing the likelihood of rediscovering known molecules. It has since evolved into the application of “explainable deep learning”, allowing for the prediction of bactericidal activity and the identification of the responsible chemical substructures leading to the discovery of entirely new classes of antibiotics [3].

Neural Network Architecture

To fully understand how this achievement was possible, it is necessary to examine why this discovery was a revolution. Traditionally, computational models represented molecules as fixed-length vectors known as fingerprints, which are derived from linear text strings such as SMILES. These representations encode the presence or absence of specific chemical substructures but fail to preserve vital information about how atoms are actually connected [2], [4]. To solve these problems,

researchers began employing Graph Neural Networks (GNNs), which learn task-specific molecular representations by modeling molecules as graphs composed of nodes (atoms) and edges (bonds). Building upon this framework, Message Passing Neural Networks (MPNNs) were introduced, allowing atoms to iteratively exchange information along bonds in order to capture both local chemical environments and global molecular structure. However, conventional MPNNs can generate redundant information loops known as totters, which reduce learning efficiency.

The Directed Message Passing Neural Network (D-MPNN) improved upon a flaw in normal MPNNs by modifying the model to pass messages along directed bonds rather than between atoms, enabling a more faithful representation of the topology as it exists in nature [4]. Using this representation, the model predicts the likelihood of antibacterial activity for a given compound, enabling the prioritization of molecules with high bactericidal potential. Thus, the model automatically learns which features are relevant for the prediction task [2].

Halicin and the Proton Motive Force Revolution

The MIT team trained the model with a dataset of 2,335 molecules with known activity against *Escherichia coli* [2]. *E. coli* was selected as a model organism because it is one of the most extensively studied bacterial species, with well characterized genetics, antibiotic susceptibility profiles and its ease of cultivation in the laboratory. The model learned to identify functional patterns within atomic relationships that predict bactericidal capacity using a Directed Message Passing Neural Network (D-MPNN) [2], [4]. Once the model was trained, it was tasked with analyzing the Drug Repurposing Hub, a library of over 6,000 compounds, with the objective of finding molecules that were chemically distinct from existing antibiotics and exhibited low predicted toxicity [2]. Through this screening process, the algorithm

isolated the compound SU-3327. This molecule had previously been investigated as a treatment for diabetes and was structurally divergent from existing antibiotics. It was subsequently renamed Halicin in honor of the AI HAL 9000, from the film "2001: A Space Odyssey" [2], [5]. This approach possesses demonstrated scalability at a level unattainable by traditional experimental methods. In a later phase, it successfully analyzed libraries of more than 107 million molecules from the ZINC15 database in just 4 days [2]. In contrast, physical screening of such a quantity of compounds would be highly costly and slow, as empirical screening is limited to a few million molecules and is impossible to perform at the scale allowed by virtual tools [2], [6]. AI allows for reducing this enormous number of candidates to only the most promising ones for physical testing, increasing the success rate while reducing cost and the time required for drug discovery [2].

Halicin is notable for its unconventional mechanism of action. Bacterial survival depends on the proton motive force, an electrochemical gradient across the cell membrane that provides the energy required for ATP synthesis. A key component of this gradient is the ΔpH , which reflects the difference in proton concentration between the interior and exterior of the cell. Unlike the vast majority of antibiotics, which inhibit cell wall synthesis or ribosomal function and are targets against which bacteria usually develop mutations for protection, Halicin disrupts bacterial metabolism by selectively dissipating the ΔpH component of the proton motive force [2]. Evolutionary experiments showed that *E. coli* did not develop resistance to Halicin even after 30 days of continuous exposure, in contrast to the antibiotic ciprofloxacin, against which bacteria developed resistance in a few days [2].

The Post-Halicin Era

Currently, this technology has been refined to address more complex and specific



problems. Contemporary models are used to predict entire structural classes of antibiotics rather than isolated molecules [2]. In a 2024 study, this approach was applied to screen over 12 million compounds, leading to the discovery of a new class of antibiotics effective against Methicillin-resistant *Staphylococcus aureus* (MRSA) and Vancomycin-resistant Enterococci (VRE) [2]. To avoid discovering potent but toxic antibiotics, current models are trained simultaneously to predict cytotoxicity in multiple human cell lines (such as HepG2, HSkMCs and IMR-90) [3], allowing for the filtering of dangerous candidates in silico via low toxicity scoring thresholds (less than 0.2) before they reach physical laboratory testing [3].

Conclusion

The integration of AI in antibiotic discovery has driven a shift, allowing a transition from limited empirical screening to algorithmic exploration [2], [6]. The success of models like D-MPNN lies in their ability to learn automatic molecular representations that

surpass the accuracy of expert-designed descriptors, facilitating the identification of compounds with chemical structures divergent from conventional antibiotics [2], [4]. This advance stands out for its scalability, enabling the virtual screening of millions of molecules within days, and also for its ability to identify revolutionary mechanisms of action, such as Halicin's dissipation of the ΔpH component of the proton motive force. Furthermore, recent evolution towards explainable deep learning, alongside the simultaneous prediction of cytotoxicity in human cell lines allows for the discovery of entire structural classes that are highly selective and safe upon initiating physical testing [3].

In a global context where 1.91 million annual deaths are projected to be directly attributable to antimicrobial resistance by the year 2050, AI represents a critical methodological framework for expanding therapeutic discovery strategies and addressing the ongoing innovation gap in anti-infective drug development [1], [6]

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Engineering Intelligence: The Role of AI in the Future of Biomedical Innovation

Over the past decade, biomedical engineering has undergone significant advancement, particularly through the integration of artificial intelligence (AI). This interdisciplinary convergence has led to the development of innovative healthcare technologies, including AI-powered prosthetics capable of adapting to users' movements through machine learning algorithms [1], intelligent medical imaging systems that analyze complex scans with speed and precision [2], and enhanced diagnostic tools that improve accuracy while reducing human error [3]. These innovations have contributed to improved clinical efficiency and patient outcomes across various medical fields.

Such progress is especially critical in addressing modern healthcare challenges, including aging populations [4], the increasing prevalence of chronic diseases [5], and limited access to quality medical care in many regions of the world [6]. As healthcare systems face growing pressure, the intersection of AI and biomedical engineering offers promising solutions that emphasize both technological efficiency and patient-centered care. This article reviews the role of artificial intelligence in advancing biomedical engineering, with particular emphasis on AI-powered medical devices, medical imaging and diagnostics, ethical and accessibility challenges, and future directions in biomedical innovation.

Foundations: Artificial Intelligence and Biomedical Engineering

Artificial intelligence is a broad branch of computer science that combines data science and advanced computational

techniques to enable machines to perform tasks that typically require human intelligence, such as learning, reasoning, decision-making, and problem-solving [7]. AI encompasses several subfields, most notably Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP). Machine Learning allows systems to identify patterns within data and make predictions or decisions without being explicitly programmed [8]. Deep Learning, a subset of machine learning, employs multi-layered neural networks to extract complex features from large volumes of raw data, making it particularly effective in image and signal analysis [9]. Natural Language Processing focuses on enabling machines to understand, interpret, and generate human language using statistical and probabilistic methods [10].

Biomedical engineering is a multidisciplinary field that integrates principles from engineering, medicine, biology, and related sciences to develop technologies that improve human health. Its scope includes areas such as biomechanics, biomaterials, biomedical optics, tissue engineering, neural engineering, and pharmaceutical engineering. Key applications of biomedical engineering include the development of prosthetics, diagnostic and therapeutic medical devices ranging from clinical equipment to micro-implants, and imaging technologies such as magnetic resonance imaging (MRI) and electrocardiography (ECG) [11].

The intersection of AI and biomedical engineering creates powerful healthcare solutions by combining AI's rapid data-processing capabilities with biomedical engineering's focus on patient-centered design. This synergy enhances diagnostics through advanced image analysis and early disease detection, supports personalized medicine by predicting treatment responses, and improves medical device development, including smart prosthetics and adaptive monitoring systems [12]. As a result, this interdisciplinary fusion enables faster, more accurate, and increasingly proactive

healthcare delivery.

AI-Powered Medical Devices and Prosthetics

In recent years, the integration of artificial intelligence into medical devices has transformed healthcare by improving efficiency, supporting clinical decision-making, and enabling personalized patient care. Among the most impactful developments are AI-powered prosthetics, which have experienced substantial improvements in design, adaptability, and functionality. These advancements enhance precision, responsiveness, and user control, significantly improving the quality of life for individuals with limb loss.

AI-enhanced prosthetics utilize intelligent algorithms to interpret nerve and muscle signals generated by the user. By analyzing electromyographic (EMG) signals from residual limb muscles, these systems translate muscular activity into electrical signals that control prosthetic movement with increased accuracy [13]. Modern prosthetic devices typically consist of terminal components such as artificial arms, legs, hands, and feet, supported by structural elements that function similarly to biological bones. The incorporation of AI enables the development of advanced human-machine interfaces, allowing prosthetics to learn from user behavior and adapt to individual movement patterns over time. Key components of AI-powered prosthetics include sensors and actuators, machine learning algorithms, neural interfaces, robotic systems, and, in some cases, cloud connectivity for performance optimization [14].

One of the most widely adopted examples of AI-driven prosthetic technology is the myoelectric prosthesis. These devices rely on EMG signals captured through surface electrodes placed on the residual limb.

When muscle contractions occur, the resulting electrical signals are processed by AI algorithms to generate precise movement commands for the prosthetic limb [15]. Advances in AI have also contributed to

lighter, more energy-efficient prosthetic designs, improving long-term usability and user comfort.

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Beyond prosthetics, AI has significantly influenced other medical devices, including implantable cardiac technologies and wearable health monitors. AI-driven pacemakers, such as implantable cardioverter-defibrillators (ICDs), employ machine learning algorithms to analyze real-time cardiac data and adapt their responses to patient-specific physiological needs, enabling earlier detection of abnormal heart rhythms [16]. Similarly, smart wearables, including smartwatches and wearable patches, use photoplethysmography (PPG) and ECG sensors to provide continuous, medical-grade monitoring over extended periods, supporting proactive healthcare management and improved patient outcomes.

AI in Medical Imaging and Diagnostics

Artificial intelligence has become a transformative tool in medical imaging and diagnostics by enabling rapid and

accurate analysis of complex medical scans, including X-rays, MRI, and CT scans. AI algorithms excel at detecting subtle patterns and abnormalities that may be difficult to identify using conventional methods, thereby supporting early disease detection, precise image segmentation, and personalized treatment planning [17].

In radiology, AI systems are increasingly

used to automate routine tasks such as image segmentation, measurements, and anomaly detection. By reducing the time required for repetitive processes, AI allows radiologists to focus on complex cases and direct patient care. This increased efficiency can shorten diagnostic waiting times, enhance screening accuracy, and improve clinical workflow, particularly in the detection of conditions such as cancer and stroke.

Importantly, AI-based diagnostic tools function as decision-support systems rather than replacements for clinicians. By integrating imaging data with patient medical histories, genetic information, and laboratory results, AI systems provide more comprehensive assessments that support personalized treatment strategies. Early detection enabled by AI-driven imaging facilitates timely medical intervention, which is often critical for improving patient prognosis and reducing healthcare costs.

Ethical, Technical, and Accessibility Challenges

Despite the rapid advancement of AI-driven biomedical technologies, several ethical, technical, and accessibility challenges remain. One of the most significant concerns is bias in AI datasets, where models reflect historical and systemic inequalities present in their training data. Much of the data used to train medical AI systems originates from high-income regions such as Europe, the United States, and China, which can result in reduced accuracy when applied to underrepresented populations. For example, AI-based dermatological tools have demonstrated lower diagnostic accuracy for darker skin tones, raising concerns about equitable healthcare delivery [18].

Cost and accessibility present additional challenges, particularly in low- and middle-income countries. While AI technologies are projected to save high-income healthcare systems billions of dollars annually, the digital divide continues to widen [19]. Many resource-limited regions lack the infrastructure, connectivity,

and technical expertise required to implement AI-powered medical devices effectively. Without intentional efforts to promote equitable access, these innovations risk reinforcing existing global health disparities. Data privacy and patient consent further complicate the adoption of AI in healthcare. Even when patient data are anonymized, the risk of re-identification remains when datasets are combined with publicly available information, posing threats to patient confidentiality [20]. Additionally, over-reliance on AI presents safety concerns, as clinicians may place excessive trust in algorithmic outputs. This dependency could contribute to diminished clinical judgment and the gradual erosion of manual diagnostic skills among future healthcare professionals [21].

Future Directions of AI in Biomedical Engineering

Looking ahead, the future of biomedical engineering is expected to be increasingly shaped by artificial intelligence through the development of hyper-personalized treatments, advanced robotic-assisted surgery, and data-driven healthcare solutions. One promising direction is the use of digital twins—virtual patient models that replicate individual biological characteristics—allowing clinicians to simulate and evaluate treatment strategies safely before clinical application.

Another emerging area is federated learning, which enables AI models to be trained across multiple healthcare institutions without sharing raw patient data. This approach addresses data privacy concerns while still allowing models to benefit from large, diverse datasets. Additionally, AI-driven drug discovery, synthetic data generation, and enhanced predictive analytics are expected to accelerate biomedical research and improve early disease detection. While these advancements hold significant promise, their success will depend on responsible governance, ethical design, and effective regulatory frameworks.

Conclusion



The integration of artificial intelligence into biomedical engineering represents one of the most significant advancements in modern healthcare. By enhancing diagnostic accuracy, supporting clinical decision-making, and enabling personalized treatment strategies, AI-driven biomedical technologies have the potential to improve both patient outcomes and healthcare efficiency. From intelligent medical devices and advanced imaging systems to adaptive prosthetics and predictive analytics, this interdisciplinary collaboration continues to redefine the boundaries of medical innovation.

However, the successful implementation of AI in biomedical engineering depends on addressing existing ethical, technical, and accessibility challenges. Ensuring transparency, data privacy, and equitable access is essential for building trustworthy and responsible AI systems. With continued interdisciplinary collaboration, ethical oversight, and thoughtful regulation, artificial intelligence can serve as a powerful tool that strengthens—rather than replaces—human expertise in biomedical innovation.

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Fig. 1. Miners haul sacks of cobalt ore at the Shabara mine near Kolwezi, Democratic Republic of the Congo. Source: Yale Environment 360 [1].

Behind the Algorithm: How Cobalt Fuels AI and Exploitation

In the 21st century, we as a society have collectively moved away from traditional search engines and have become adamant users of artificial intelligence chatbots. This growing reliance on chatbots by humankind has become a true testament to their role as key providers of information, resources, and guidance. Bots like Claude or ChatGPT have taken on the roles of data analysts, financial forecasters, and radiologists, and have simply become a vital aspect of our day-to-day lives [2]. Although many developed nations have indeed realized the extensive benefits of chatbot implementation, it is essential to acknowledge that some societies have worsened with every generated response. Many nations, specifically those that contain the minerals needed to power AI technologies, have faced extreme exploitation and human rights violations [3]. Yet, at the present state of scientific knowledge, there are no adequate substitutes for such minerals, especially cobalt [4]. Therefore, an understanding of the properties of cobalt is crucial when developing potential alternatives and determining which next steps in

technological enhancement should be prioritized by the scientific community.

What most users are unaware of is that every AI chatbot, automated assembly line, and data-processing center is a complex hardware system that is powered through various minerals. One of the most important ones is cobalt, which is used in lithium-ion batteries and magnetic alloys of semiconductors to support their motors, cooling systems, power regulation, and data centers [5]. Cobalt, with an atomic number of 27 and a symbol of Co on the periodic table, is primarily sourced from ores such as cobaltite and erythrite, and from byproducts of copper and nickel mining [6]. Its selection as a crucial mineral in the development of AI technologies was primarily a result of three reasons: its high melting point at 1495 degrees C, its ferromagnetic properties due to unpaired electrons in the 3d orbital, and the fact that it is abundant in regions within the cobalt belt [7], [8]. Not to mention that cobalt alloys also have an extremely high corrosion resistance, due to their ability to form a stable, self-healing passive oxide layer, a direct result of their high chromium content. Hence, the material can prevent oxidation when used in large-scale magnets in varying applications, including industrial

controls and aerospace systems, and can maintain its strength in high temperatures where other metals may degrade [9].

As its chemical properties are highly suited to large-scale AI systems, its demand in the current global economy has increased, along with exploitation and human rights violations in producer nations. For instance, the Democratic Republic of Congo (DRC), despite being incredibly rich in cobalt, is ranked as one of the poorest nations in the world. The DRC's cobalt exports alone total \$4.44 billion, representing 68% of the world's cobalt, yet the mean income for a Congolese person is a mere \$449 per year [10]. This discrepancy can be attributed to corrupt leaders prioritizing the expectations of larger nations and disregarding the needs of their citizens, which is highlighted by that nation's 163rd position on the corruption index [11]. Specifically, the expansion of the industry has caused officials to establish large mining concessions throughout the nation, often demolishing local infrastructure and displacing local populations. This, in turn, leads civilians to turn to artisanal mining as a source of income; a hazardous practice where workers use basic tools instead of industrial methods to extract metals such as cobalt, tin, tungsten, and tantalum. As this type of mining is an informal aspect of the economy and lacks proper monitoring, local Congolese people often face abuse from employers, sexual harassment, and no medical compensation for injuries sustained while digging for cobalt. Many have suffered from harmful medical side effects from living near cobalt mining facilities and have even died due to unsafe mining protocols [12]. All of which are practices that have broken several Human Rights laws, including Articles 3, 4, 5, 23, and 24 as outlined in the Universal Declaration of Human Rights [13]. These violations mostly correlate to cobalt's role in powering and cooling the infrastructure that supports semiconductor-based AI systems, including data centers and energy storage technologies [14].

It is important to recognize that while the

chemical properties of cobalt make it invaluable for current AI technologies, it is not the metal's use that inherently causes exploitation. Rather, the human rights violations in producer nations are a consequence of demand-driven economic pressure and government failures. This argument highlights a correlation between cobalt demand and exploitation rather than a direct causal relationship. To decrease this excess demand, the use of cobalt in AI technologies must be reduced, and it is the responsibility of the scientific community to find possible alternatives based on cobalt's chemical properties. One currently proposed alternative to cobalt as an energy storage material is bis-tetraaminobenzoquinone (TAQ), a cathode material that has been slowly incorporated into the EV industry. This organic small molecule contains three fused hexagonal rings, and its layers can extend outward in every direction, forming a structure similar to graphite. Present within the molecules are chemical groups called quinones, which are the electron reservoirs, and amines, which enable the material to form strong hydrogen bonds. These bonds make TAQ highly stable and extremely insoluble. This property of insolubility is important because it prevents the material from dissolving into the battery electrolyte, which extends its lifetime. When tested and compared with traditional cobalt-containing batteries, TAQ showed promising results as its conductivity and storage capacity were similar to those of the metal. [15].

As AI is increasingly incorporated into day-to-day lives, data-processing centers will need to double their power consumption, with minerals such as cobalt as essential components in maintaining the expansion of digital infrastructure [16]. If we can understand what core characteristics of the metal make it as valuable as it is, we can then seek alternatives to reduce the burden on producer nations and their workers while still maintaining the development of Artificial Intelligence. At the current level of scientific innovation, cobalt's vital role in the artificial intelligence industry stems from its thermal stability, electron

configuration, and degradation resistance. Understanding such core properties allows scientists to identify alternative materials that replicate cobalt's functions without relying on mining practices. Materials such as bis-tetraaminobenzoquinone (TAQ) have already demonstrated promise in energy storage applications, as their quinone-based molecular structure enables

stability and high-energy bonding capabilities. Hence, the development and discovery of such materials illustrate how scientific research surrounding the properties of essential metals can reduce dependence on cobalt, thereby alleviating pressure on producer nations while maintaining the development of artificial intelligence

By Renee Sharapov

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How AI Spots What Humans Miss

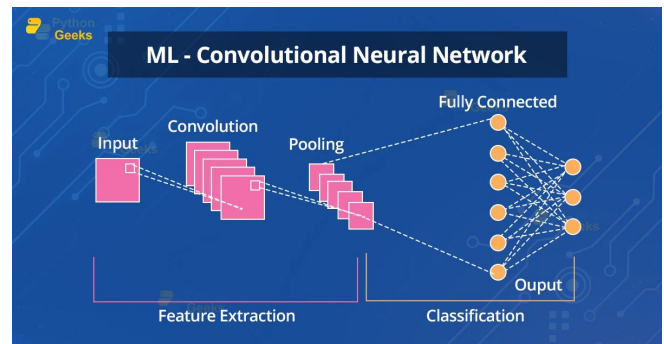
Artificial Intelligence (AI) has rapidly expanded across major fields in healthcare, especially through its implementation in medical imaging programs. Images doctors used to diagnose and treat disease could only be read by trained specialists in the past. However, breakthroughs in these machine learning models make it possible to detect subtle traces of disease such as cancer, without the risk of human error. This makes it possible to transform the way that illnesses are discovered in the body and treated [1]. As a result, this new technology allows healthcare professionals to focus on early intervention, rather than active procedures, offering new possibilities for improved patient outcomes.

Technology Behind the Breakthrough

These AI models are built by using a technique called deep learning, where networks are trained on databases of medical images. The model studies the examples given for training until it can correctly identify each condition [2]. Exposure allows this model to learn rare disease cases and even subtle abnormalities that physicians may only encounter a few times in their careers. Once trained, advanced systems can analyze medical images far beyond human capacity, identifying patterns invisible to the naked eye [3].

Some deep learning models, such as convolutional neural networks (CNNs), learn what is considered an irregular feature during training [1]. CNNs scan images using filters that detect variations in edges, shape, and texture, rather than relying on manually

engineered rules. This model scans in layers, starting with simple line or brightness changes, while deeper layers search for complex features [3]. The layered approach lets AI uncover abnormalities early, especially making a difference in early-stage disease diagnosis.



Early Onset Analysis

The main reason AI outperforms humans in medical imaging is because of feature extraction, where visual patterns are recognized that reveal disease long before humans are able to detect them. This shifts healthcare from reactive to proactive. Rather than waiting for a condition to become severe enough for a diagnosis, this technology gives clinicians a head start and allows them to intervene, known as early-onset analysis [4].

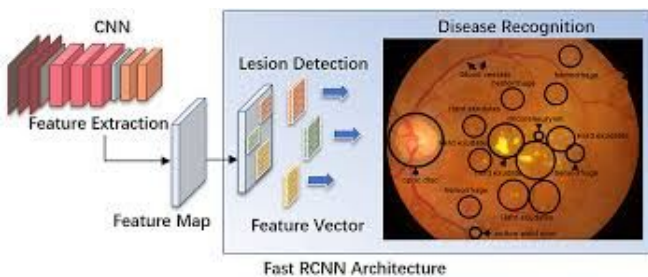
Another factor that is useful in using machine learning models for imaging is the ability to analyze massive amounts of data with consistency and speed. Compared to human readers whose performance can vary due to fatigue, these systems maintain the same amount of accuracy across thousands of images. This not only accelerates diagnosis, but supports more standardized care, especially in settings where trained specialists are limited [3].

Beyond the initial diagnosis, early-onset analysis supports long-term monitoring. Since AI can detect small changes in tissue structure or density over time, it can also track how a disease is progressing or whether it is responding to treatment with greater precision than human interpretation alone [5]. This continuous surveillance aids medical professionals in adjusting treatment

plans for individual needs, personalizing care more effectively.

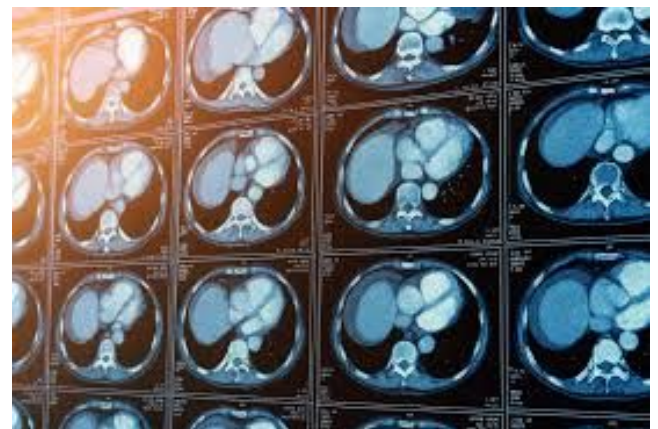
Real-World Applications

AI has moved past experimental models and is currently being used in clinical practice across multiple specialties [3]. Often, hospitals rely on systems that automatically flag scans that show high risk of disease, allowing patients to receive faster and more effective care. In ophthalmology, this technology has become a tool for analyzing retinal images. Deep learning models can use these images to detect diabetic retinopathy, glaucoma indications, and age-related degeneration of the eyes [6]. This has enabled underserved regions with ophthalmologist scarcity to have access to the same care, expanding access to early eye-disease insight.



In addition, AI is transforming pulmonary imaging. In hospitals, these models are being automated to scan X-rays and CT images for signs of lung disease, such as pulmonary nodules, emphysema, pneumonia, and other abnormalities [1]. Clinicians use this tool to manage imaging backlogs, faster decision making in emergency settings, which overall reduces delays in diagnosis. However, one of the most important functions improved by this technology is efficiency in screening. When a patient arrives with critical symptoms, their symptoms can be rapidly analyzed and provide assessment within seconds. This ensures that patients with life-threatening conditions can receive timely intervention and improves long-term outcomes. Cardiology has seen similar advancements. Technologically enhanced cardiac MRI tools can measure chamber sizes, detect subtle abnormalities, and provide assessments for conditions such as heart failure,

cardiomyopathy, and valvular disease. These systems use automated measurements that reduce variability between diagnosis and provide consistent assessments [4]. An example can be seen in this technology supporting healthcare equity. Many demographic groups, particularly those in low-resource hospitals or communities face delays in diagnosis due to a shortage of expert readers. However, by reducing dependence on specialist availability, AI expands access to quality healthcare, improving results for historically underserved populations.



Challenges in Clinical Adoption

Despite its rapid technological processes, integrating AI into clinical imaging worldwide remains challenging due to a number of factors. One of the biggest obstacles is the fragmented nature of medical data, with records varying widely across different hospitals and devices. This makes synchronized performance difficult in a global setting [3]. Clinicians also express hesitation through concerns of liability and patient consent, since this tool operates by giving sole answers without much clarification, known as limited explainability. Even when this technology performs well in controlled studies, these same systems can fail to replicate accurate results in clinical environments due to differences in patient population, constraints, and imaging protocols [7]. Concerns about cybersecurity and data privacy also persist, especially with platforms relying on external data storage or cloud-based processing. Both of these require sending patient images outside the hospital's own servers which

risks breaches [7]. However, this machine intelligence remains a valuable tool because its benefits consistently outweigh the limitations. The ability to enhance accuracy, provide early-onset analysis, and support overburdened physicians make it an essential complement to traditional imaging rather than a replacement.

A New Partnership

We see a new partnership emerging in modern healthcare, one where humans and AI systems work together.

AI excels in analyzing complex imaging data, but human expertise interprets these findings into context of a patient's history and symptoms. Instead of replacing specialists, AI acts as an extension, catching patterns that may easily slip due to human error, allowing for a better focus on treatment planning [2]. This collaboration represents the future of medical imaging, where technology enhances healthcare, ensuring patients receive the best possible outcomes.

By Faliha Tariq

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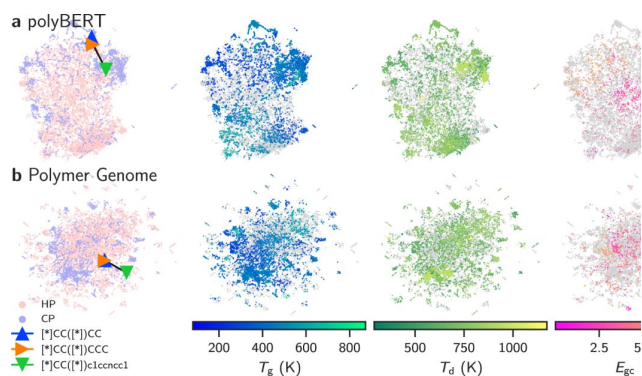
AI in Polymer Design

Toys, bags and bottles are everyday items that are rarely seen as chemical achievements. Yet most of these are made of the same polymer, polyethene, which accounted for 116.35 million metric tonnes of products in 2024 alone according to industry estimates [1]. Designing and optimising polymers traditionally requires years of painstaking trial and error. The development of polyethene for instance, took 6 years of intensive research [2]. Today, polyBERT and other AI models, can generate polymer fingerprints and predict properties hundreds of times faster than conventional experimentation [3]. AI is no longer simply assisting chemists; it is reshaping how polymers are designed and understood.

Models like polyBERT use a range of techniques, from neural networks and spectroscopic polymer analysis to machine-learning driven FTIR and Raman identification to achieve this [4]. Polymers have to be represented numerically, using SMILES strings which are small, text-based strings that show chemical structure; molecular graphs, which show trends and even 3D structures [5]. SMILES strings and molecular graphs represent the 2d chemical topology of a molecule, while the 3D structures provide full spatial geometry derived from that topology.

Once the data is encoded, using neural networks, softwares are able to predict the properties of designed polymers. These networks are given carefully curated databases, and are able to adjust weighted

connections between nodes, similar to how our brains process data. By linking input values to a weight and a bias value, the network is allowed to recognise patterns and infer molecular properties accurately. From these numerical values, the network infers properties through probability. Using its machine learning to train these models, they learn to detect anomalies, classify patterns and process natural language at very fast rates [6].



Materials research used to depend on reactive, trial and error experimentation and analysing polymer synthesis. AI enables us to accurately characterise new materials before production in a much more efficient manner. This results in fewer wasted materials and failed batches, and a dramatically accelerated path from designed concepts to practical application.

Synthesising these polymers increasingly begins not in the laboratory, but with a research prompt. Using an inverse design approach, researchers are able to define their desired properties for a material (e.g. functional group placement) and the model suggests corresponding chemical structures to optimize specific features e.g. cross-link density [7]. It allows researchers to easily optimise and commercialise their products making it significant compared to traditional synthesis. The materials can be designed for purpose and the benefit of the world, and rather than modifying existing materials, the generative models are proposing polymer compositions that humans would not think of intuitively.

This has already attracted industrial interest. Toyota, for instance, chose to speed up their R&D process by using AI models to design the electrolytes for solid-state

batteries. The models identified and included a complex arrangement of different atoms, incorporating elements like phosphorus and nitrogen in sequences, rather than just maximising oxygen content. These designs balanced ionic conductivity, stability and manufacturability more effectively than traditional approaches [8]. Another industry using machine learning to create polymers is the bioplastics sector, with companies like Senbis partnering with TNO to link data science algorithms and materials to create a biodegradable polyester for textile fibres in clothes to mitigate the microplastic pollution created by synthetic fabrics [9]. As varied as a car company and a sustainability company are, they both utilise AI in chemistry to produce positively impacting materials for their products efficiently. While Senbis remains mainly in scientific research, Toyota plans to commercialise their product, proving how many uses AI has.

The ultimate goal of the integration of machine learning with these experimental platforms is to create a fully autonomous system. Through these polymer design, synthesis and characterisation can occur within a continuous feedback loop, allowing models to learn directly from their own experiments and refine neural connections, with little human intervention [9]. As of now these systems must operate under supervised learning methods, where chemists and engineers monitor outputs to correct errors and restrict exploration to prevent unsafe materials being produced [6].

As polymer synthesis is increasingly reducing human intervention, the integration of AI within materials science extends beyond efficiency to sustainability and environmental impact. Engineers are able to use machine learning degradation behaviour simulations to simulate how polymers will break down under various environmental conditions such as temperature or microbial activity. These are softwares that use data to understand how products break down in nature, which allows scientists to avoid toxic residues,

and look at environmental impact accurately [10]. By forecasting these pathways before production, chemists can design polymers with controlled lifespans and create biodegradable materials that are easier to recycle chemically, fundamentally changing how environmental engineering is embedded in materials science.

Beyond material design, recent models have been used to assist in manufacturing planning, to design efficient, more affordable pathways. This ensures that generated polymers can be realistically produced on an industrial scale using available monomers and catalysts to minimise energy consumption and material waste [11].

Artificial intelligence also plays a critical role in closing the loop at the end of a polymer's life. Models have been used to accelerate life cycle assessments (LCAs, which define environmental impact of a product from its production to disposal) before synthesis. Spectroscopy machine learning is used to conduct AI-assisted polymer sorting to identify mixed plastics in recycled feedstocks and reduce contamination [12]. This leads to higher recycling yields, addressing one of the most significant challenges in plastic sustainability. It links chemical and materials science engineering effectively and enables the polymer circular economy: a model where polymers are continuously reused, repaired and recycled [13]. Less than 10% of global plastic waste is currently recycled, highlighting the scale of the challenge that AI-assisted polymer design aims to address [14].

As AI reshapes how polymers are designed, it changes how responsibility and authority are distributed in materials science. It is essential to focus on the ethical implications of integrating AI into chemistry to use it as a tool, rather than let AI expand into harmful regions.

Using AI shifts the roles of chemists from conducting hands-on experiments and brainstorming in the lab, to becoming interpreters of models. AI reduces direct lab interaction, especially in early-stage

research; which truly changes the meaning of being a chemist. Traditionally, chemists build intuition through repeated synthesis, failure and improvements and studying chemical properties. As AI begins to slip into materials science, it creates revolutionary change with faster innovation and deeper conceptual understanding. However, chemists are increasingly led to validate and interpret outputs rather than generate them, raising concerns about the gradual loss of understanding and practical skills within the field. Although AI can outperform humans at pattern recognition across large datasets and work at greater speed, over-reliance may weaken reasoning [15]. It requires careful governance to prevent the fundamentals of chemistry being forgotten, raising critical arguments about whether the models enhance expertise, or replace it.

If our reasoning weakens, spotting and understanding errors will become more difficult, leading to issues of accountability. Models are often blackbox systems, meaning engineers cannot directly understand its reasoning. This means that if a polymer fails structurally, the responsibility must be distributed between developers, researchers and manufacturers. Polymer failure has real consequences, hence, this introduces great ethical responsibility. Similarly, AI designs are only as good as the data they are trained on, and that data has

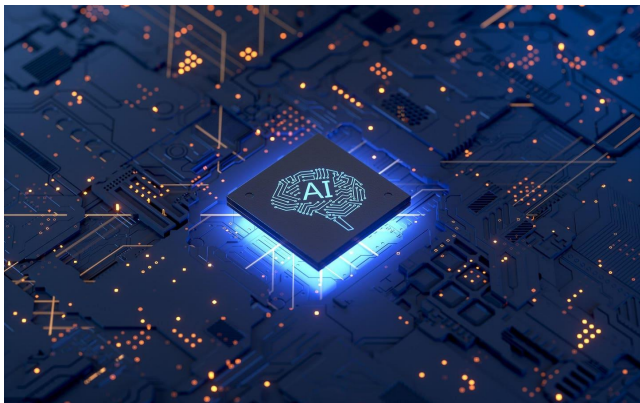
limitations. Existing polymer datasets often over-represent commercially successful materials [16], [17]. Models may reinforce existing material choices rather than identifying genuinely sustainable alternatives. As a result, optimisation may prioritise performance and cost over environmental impact. Without carefully designed objectives, AI risks accelerating existing unsustainable methods, rather than fixing them.

To conclude, AI is transforming polymer science from a field defined by slow experimentation, into one driven by optimisation and data-led design. From spectroscopy based characterisation to inverse polymer design, AI accelerates discovery and supports sustainability. It is not merely assisting chemists, but is a tool reshaping how materials are produced. However, this shift introduces ethical and professional challenges. As chemists increasingly interpret and supervise models rather than generate ideas experimentally, concerns arise around expertise, responsibility and dependency on these algorithms. Biased datasets may also reinforce existing unsustainable material choices rather than challenge them. The future of polymer science therefore depends on balance. AI must remain a tool, guided by chemical insight and ethical responsibility, enhancing and not replacing human expertise.

By Shrishti Singh

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Wired Intelligence: How AI Is Rewiring The Future Of Electronics

Artificial Intelligence is no longer software in the cloud. It is increasingly anchored to the physical world through circuits, sensors and power systems. The convergence of AI and EEE(Electrical and Electronic Engineering) produces tangible outcomes that could be perceived from ML-assisted chips to neuromorphic processors. In the world of computing, we have also seen an exponential increase in the price of RAM as a result of AI companies. This is evidenced by algorithms, once confined to data centres, now being embedded in sensors, microcontrollers, and power systems.

AI in Electronic Design and Automation

AI-driven Electronic Design Automation (EDA) systems are typically evaluated using Power, Performance and Area metrics (PPA). PPA is also the three primary metrics used to evaluate the overall quality of a semiconductor design. In chip floorplanning and placement, reinforcement learning models have demonstrated reductions in total wire length of up to 10-20%, alongside measurable improvements in timing closure and power efficiency when compared to traditional heuristic-based methods [1]. Miroseini et al. reported that graph-based reinforcement can generate layouts in a matter of hours that match, and in some cases exceed, the PPA performance achieved by human engineers after several weeks of manual design.

Beyond placement, AI is increasingly applied across the Integrated Circuit (IC) design pipeline. Neural networks are used for analogue circuit sizing, where

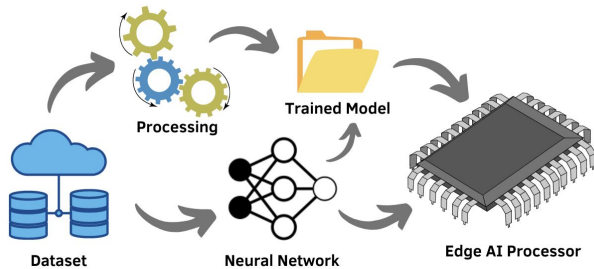
continuous parameter spaces make traditional optimisation difficult. Machine learning models also assist in logic synthesis, routing congestion prediction, design rule checking and fault detection during verification. Examples for this being incorporated in technology today involve Cadence's Cereberus Intelligent Chip Explorer that uses reinforcement learning to predict routing congestion early. It explores the design space, tests different placement and routing strategies, and receives feedback on power, performance, area and congestion. Over many iterations. In reliability engineering, AI-based anomaly detection can identify potential failure modes early in the design cycle, therefore reducing costly post-silicon fixes.

Embedded Intelligence and Edge AI

Edge AI is the practice of running AI algorithms locally on a hardware device like a sensor rather than on a remote cloud server. This reduces latency and improves privacy. Edge AI embeds inference on small, low-power platforms so that devices can make decisions locally. Wearable health monitors that can run lightweight models locally can detect abdominal heart rate patterns in real-time without streaming raw biosignals to the cloud [2]. Edge AI systems operate under severe resource constraints, often limited to kilobytes of Static Random-Access Memory (SRAM) and power budgets below 100mW, requiring aggressive model optimisation. To enable machine learning inference on microcontrollers and System-On-Chip (SoC) platforms, several optimisation techniques are employed. Quantisations (converting infinite values into a finite set of discrete values) reduce numerical precision from floating point to fixed point representations such as INT8, significantly reducing memory usage and energy consumption.

From an Electrical and Electronic Engineering perspective, embedded intelligence extends beyond software optimisation. Sensor interfacing, analogue signal conditioning, and analogue-to-digital conversion (ADC) play critical roles in

determining system accuracy and latency. In many edge systems, partial signal processing is performed in the analogue domain before digital inference, therefore reducing data throughput and power consumption. This intersection of hardware front-ends with machine learning models illustrates how EEE principles underpin the practical deployment of Edge AI.



Neuromorphic Hardware: Physics Meets Spiking Networks

Neuromorphic Engineering is a field of engineering that attempts to reproduce properties of biological neural circuits, event-driven computation, sparse communication, located memory, and processing. The Loihi processor from Intel Labs demonstrates an improvement of over three orders of magnitude in delay product [3]. Emerging devices such as memristors - memory resistors that retain the amount of electrical charge that flowed through them after power is turned off - provide non-volatile, analogue resistance states, enabling dense synaptic storage with energy consumption orders of magnitude lower than Complementary Metal Oxide Semiconductor (CMOS) based memory. Neuromorphic processors such as Intel's Loihi are optimised for Spiking Neural Networks (SNNs), featuring distributed memory colocated with computation and asynchronous communication between neuron cores. In contrast, GPUs rely on dense matrix operations, global memory access, and synchronous clock-driven execution. While GPUs excel at high-throughput training of deep models, they suffer from significant energy overhead due to data movement between memory and processing units. Non-recursive

architectures achieve orders of magnitude improvements in energy efficiency for suitable workloads as they eliminate unnecessary data transfer.

AI for Power Systems and Smart Grids

AI techniques such as time-series forecasting, anomaly detection, and reinforcement learning are utilised for demand forecasting, renewable integration, and predictive maintenance [4]. For example, long short-term memory networks are used to model temporal demand patterns, enabling utilities to anticipate peak loads with increased accuracy. In terms of grid stability, RL algorithms are being explored for frequency regulation and voltage control in networks. However, the integration of AI into safety-critical infrastructure introduces ethical and technical challenges. Black Box models (AI models that produce outputs but internal logic and decision-making are kept hidden from humans due to their complexity) may produce decisions that are difficult to interpret, raising concerns about accountability and trust. Engineers must prioritise robustness and fail-safe operations to ensure that AI-enhanced power systems remain secure and reliable under normal and fault conditions. The integration of AI into critical infrastructure requires a robust security framework. As AI becomes increasingly embedded in physical hardware, it needs to be protected from tampering or side-channel attacks that may result in data being compromised. In power systems and smart grids, AI models must be secured against attacks where small malicious data inputs can bring about large-scale grid instability. For safety-critical EEE applications, moving away from black box models toward interpretable AI ensures that engineers can verify why a decision was made, which is essential for auditability and risk management.

Case Study: AI-Driven Chip Placement and Neuromorphic Acceleration

Graph-Based RL has been applied to chip floorplanning, with Mirosenhi et al. framing

placement as a reinforcement learning problem and generating layouts in under six hours that rival human experts [1].

Similarly, neuromorphic cores and on-chip learning achieve up to 1000x improvements in energy delay efficiency [3].

These case studies demonstrate AI's dual role in modern electronics and the significant impact it has on EEE. AI-driven chip placement demonstrates how machine learning can enhance the efficiency and quality of hardware itself, while neuromorphic processors such as Loihi embody AI as a native feature of hardware operation. These methods both aim to reduce energy consumption, improve performance, and minimise human intervention. However, these technologies face limitations: RL-based design tools require extensive training data, and neuromorphic processors lack widespread software support and standardisation. In addition, challenges remain in scalability and programmability. Collectively, both case studies demonstrate the powerful role AI plays in modern electronic design and implementation.

Technical Sidebar: Neuromorphic Processor Architecture

Table 1: Comparison Of Key Architectural Figures: CPU, GPU and Neuromorphic Processor (Loihi)

Feature	CPU	GPU	Neuromorphic Processor (Loihi)
Computational Model	Sequential	Parallel	Event-driven
Memory location	Separate	Partially shared	Co-located with compute
Energy Efficiency	Low-Moderate	Moderate	Very High
Ideal Workloads	Control, logic	Dense ML training	Sparse real-time inference
Clocking	Synchronous	Synchronous	Asynchronous

Loihi(Intel 0-14 nm Complementary Metal Oxide Semiconductor (CMOS), ~130k neurons, ~130M synapses) leverages an asynchronous mesh architecture to achieve over 1000x energy-delay improvement, featuring event-driven spikes, collated memory, hierarchical sparse connectivity, and on-chip learning [3], [5].

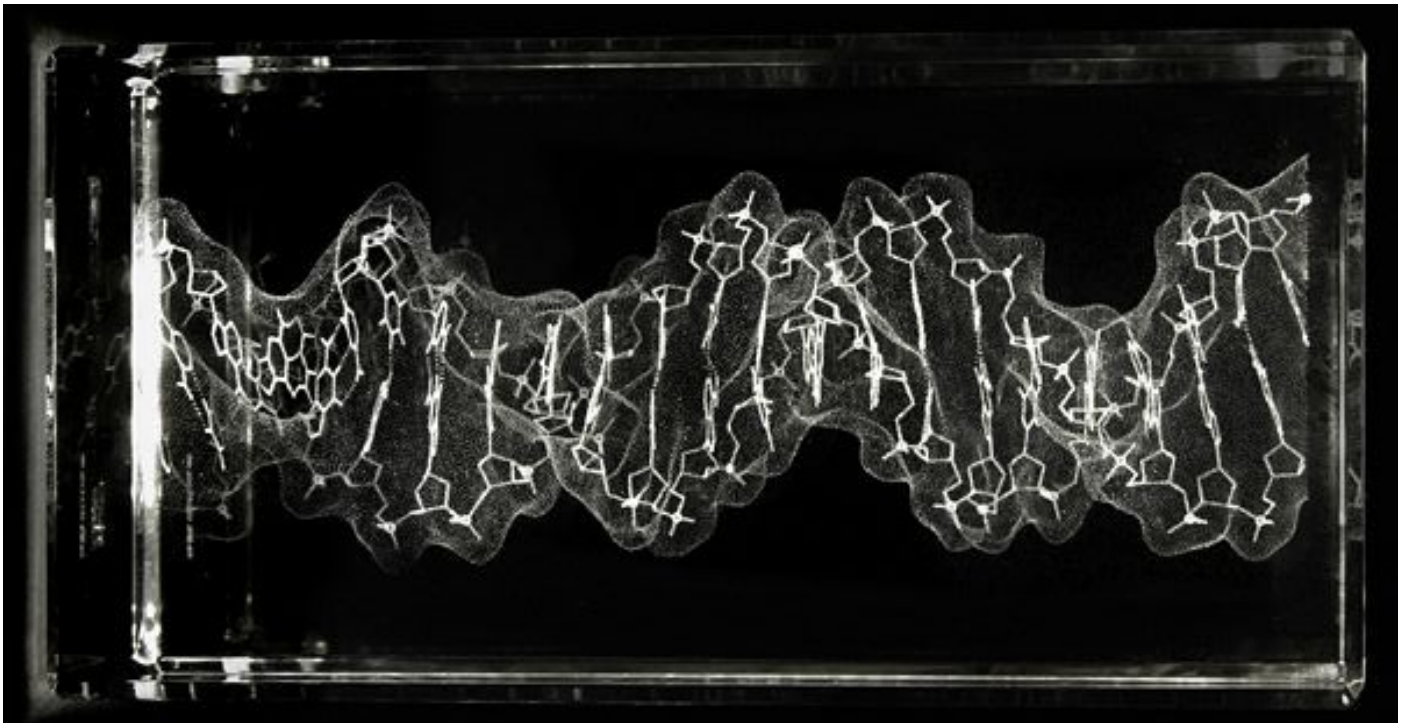
Discussion and Conclusion

The convergence of AI and EEE demands hybrid skill sets. Today, many universities are incorporating Artificial Intelligence modules into engineering degrees, for example, the University of Surrey for undergraduate and postgraduate degrees. Circuit design, embedded systems, and data engineering are examples of areas where the intersection of AI and EEE becomes evident. Engineers must ensure ethical and robust integration as intelligence becomes embedded in physical systems [4]. Statistics from Sanderson Recruitment show that AI usage worldwide has increased from 45% in 2024 to 71% in 2025 among globally surveyed engineers [6].

Ultimately, the deepening convergence of AI and EEE suggests that these technologies will no longer be viewed as separate disciplines; rather, AI is poised to become a foundational pillar of both industrial practice and university engineering curricula. As intelligence migrates from centralised data centres to embedded, safety-critical systems, Electrical and Electronic Engineering will become the discipline through which Artificial Intelligence physically manifests in the world. The contribution to the environment that technologies like neuromorphic processors offer is a 1000x improvement in energy efficiency compared to traditional processors [5]. This reduction in power consumption is critical for scaling AI without an unsustainable increase in global energy demand. For users, these advancements manifest as longer battery life in more responsive environments and wearable health monitors that can provide life-saving alerts in real time without needing a constant internet connection.

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The Fusion of AI and Genomics: Unlocking Precision Editing

Genome editing over the past few decades has become a viable approach for treating various diseases. Its rapid development can be attributed to various modern technologies including Artificial Intelligence (AI). From expediting genome sequencing to optimizing the precision of revolutionary technologies such as CRISPR-Cas9, AI has played an integral role in transforming genomics [1]. These technologies are not only tools aiding scientists in the further development of gene-editing technologies; rather, it is entirely reshaping how we interact with the genetic makeup of life.

The Evolution of Genomic Data Analytics

A single genome contains approximately 3 billion base pairs, and a single cell in the human body contains approximately 750 megabytes of data; by using technologies such as next-generation sequencing (NGS), thousands of petabytes of data can be generated from a single human [2]. Previously, genome sequencing was incredibly tedious and expensive. For instance, the Human Genome Project—a project that aimed to sequence the first human genome—started in 1988 and ended in 2001, taking nearly 13 years to complete [3]. Despite this breakthrough, genomic sequencing was still unable to provide for

the development of genomic medicine at a large scale due to high costs.

However, the implementation of machine learning (ML) and deep learning (DL) algorithms allowed for the acceleration and feasibility of genomic sequencing and analysis, thereby reducing the cost of sequencing a genome from one hundred million dollars to less than one thousand with two decades [4].

Machine learning algorithms sift through genomic data to identify patterns and connections between genes and disease. Two overarching models of machine learning are often used: black box and open box [5]. Black box models are incredibly powerful and accurate as they label genes exactly. However, to achieve this, they require massive amounts of data and lack transparency in how the relationship is established—thus, being deemed as “opaque” [6]. On the other hand, open box models instead utilize multiple interpretable models that create a “scaffolding” that explains the relationship between the genomic data and diseases allowing for researchers to identify patterns and connections that they would not have been able to identify with a black box model [7].

Now, as more complex AI systems emerge, they create a much greater scope in deciphering complex genomic data. Deep

learning models integrate data from various aspects of genetics, allowing for greater insight into genes and their roles in disease [8]. For instance, AI in proteomics—the study of the proteins produced in cells—allows researchers to bridge the gap between genes and proteins, leading to a more nuanced understanding of genomics [9].

They also uncover various other factors including gene-to-gene interactions, gene expression levels, and environmental influences which can enable risk prediction and contribute to functional genomic studies [8]. Large language models (LLMs)—the most advanced AI system that exists today—treat DNA sequences as a language and can be fine-tuned to specific tasks such as variant calling, gene annotation, and motif discovery [10].

AI not only allows scientists to process large amounts of genomic data, but also further analyzes it to understand gene functions and predict gene interactions which can lead to the development of life-saving treatments for terminal diseases.

AI as a Transformative Tool in CRISPR

Although, the first successful gene-editing treatments using CRISPR-Cas9 have been well underway, there are still various obstacles that need to be addressed before gene manipulation becomes widespread.

CRISPR-Cas9 is a bacterial immune system repurposed for precise genome editing. By using a guide RNA (gRNA) the Cas9 nuclease binds to the target and unwinds the DNA helix, cleaving both strands. Afterwards, using base-pair complementarity, the complex “edits” the gene [11].

One of the many implications of genome manipulation, is the potential of off-target effects which could have serious health consequences. AI models improve upon this issue by refining the design of gRNA and denoting their on-target activity through cleavage efficiency prediction and modeling editing patterns, resulting in the most

optimal gRNAs [12]. These models can indicate off-target effects which are crucial for enhancing the safety and specificity of the CRISPR-Cas system and allow researchers to choose a gRNA with both optimal on-target efficiency and minimal off-target effects [13]. In practice, AI models predict editing outcomes such as deletions and insertions. These simulations help visualize scenarios that attain desired results and reduce unintended mutations. Furthermore, AI aids in developing and choosing optimal Cas variants for experiments [14]. Employing simulations reduces development time for therapies targeting rare genetic disorders. The goal is not to create a single most efficient method but rather find the most optimal option for a specific gene of interest while also keeping genomic context in mind.

Recently, researchers at Stanford Medicine developed an AI tool that helps scientists better plan gene-editing procedures. CRISPR-GPT acts as an AI copilot, helping researchers—even those unfamiliar with CRISPR technologies—design and execute gene-editing experiments with unprecedented accuracy [15]. This has revolutionized the pre-wet lab process and gives rise to the possibility for gene-editing experiments to be completed in a single trial, increasing accessibility and viability of gene manipulation.

Due to the implementation of AI models, the uncertainty surrounding the relative effects of cutting a gene is reduced by nearly 95% most recent systems [16].

Personalization of Treatment with AI

AI has the computational power to interpret vast amounts of genomic data. Using this information, AI can identify specific mutations and biomarkers that put a person at risk of a disease [17]. Because scientists can identify high-risk individuals, they can then catch diseases in early stages or even implement preventative measures reducing the mortality of many terminal diseases. AI achieves this by comparing individual genomes against population databases and

combining proteomics and clinical data to form a holistic diagnosis [18]. Using an in-depth analysis of genomic data, patients can receive personalized treatments and find an optimal option for them.

For rare diseases, AI integrates genetic profiles with phenotypic data, suggesting novel edits. This powers initiatives like the Sanger Institute's Cancer Dependency Map, combining AI with gene editing for drug target discovery [19]. Ethical AI frameworks further protect genomic data privacy during analysis.

AI—especially LLMs—generate predictions and interpretations based on previously available genomic data; however, much of the available data is extremely Euro-centric, causing a lack of diversity in genomic data [20]. This poses the risk of inaccurate results as the genomic context may be lacking in generated diagnoses.

Endless Possibilities of AI

However, the influence of AI technologies on genomics does not end there. It also pioneers synthetic genomics, facilitating the modeling of novel genetic material with desired functions that can create new proteins and enzymes [21]. Synthetic genomic datasets can enable broader research and modeling without compromising patient privacy.

The benefits of AI and genomics also extend beyond gene manipulation in

humans. It also serves as a transformative tool in the fight against the global health crisis of increasing antimicrobial resistance (AMR). AI accelerates the process of identifying and synthesizing novel antibacterial compounds in order to combat evolved microbes [22]. It accomplishes this by converting vast biological and chemical data into drug candidates with high probability through prediction models [23].

Challenges in further development of AI technologies in genomics remain, however. There are various ethical concerns regarding patient privacy, algorithmic biases, and a lack of transparency [24]. Algorithmic bias occurs when datasets favor “healthy” patients, excluding minorities and diseased patients which can cause poor generalities reducing the efficacy of treatments [25].

The Future of AI in Genomics

Soon, genome manipulation could give rise to on-demand therapies, engineering crops for climate resilience, or even germ-line gene editing. These technologies not only help us deconstruct the language of life but also can give us the power to rewrite it ourselves safely and ethically. AI can be used to propel progress in gene editing but also act as a safeguard against possible eugenics through machine learning-derived restrictions [26]. Genomics, with the power of AI, has the potential to save lives across the planet.

By Nyshita Nuli

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The Use of AI in Drug Discovery: A Potential Tool to Revolutionise the Industry

Drug discovery has always been limited by the complexity of biology. It can take 10-15 years to bring a new treatment to the market, and screening of medicines can cost billions of pounds. AI can be used to identify targets such as genes or proteins which are involved in the disease process. They can also help to predict toxicity and find promising candidates for testing. The introduction of AI into the world of drug discovery could drastically reduce manufacturing time and allow scientists to produce new therapies that are more affordable and therefore more accessible to the general public [1].

To understand how AI can aid drug discovery, it is necessary to outline the stages of the drug development process. In the pre-discovery stage, researchers identify proteins that may be involved in the disease process. They then form a hypothesis that inhibiting or activating a particular protein could help to treat the condition. Proteins are the most common area for drugs to target, but the drugs can also target DNA or RNA. The target area chosen is the one whose activity is linked to the disease, and that activity can also be modulated by a drug. Next, scientists will search for a molecule that will work on the specific target chosen. 'Rational drug design' is a method in which scientists use knowledge of biological targets and chemical properties to create new molecules specifically tailored to treat diseases effectively. This process combines

chemistry and biotechnology to develop these targeted drugs. Another option is to choose an existing molecule from a large selection of previously synthesised potential candidates, manufactured during other drug discovery journeys. The molecule is then tested by building it into compounds with different combinations to determine which is most effective. Once the best molecule is chosen, it is meticulously tested to assess safety, stability, and reproducibility. It can be tested *in silico* (on computers), *in vitro* (in test tubes), and *in vivo* (in animals). Pharmaceutical teams then convert the molecules into safe medicines for clinical trials. They must take into consideration many questions, such as the dosage, how it will reach the target area, and its form. During clinical trials, there are four phases. The first stage involves a group of healthy participants to test the safety and tolerability of the treatment. In phase II, a large group of patients with the disease are given the drug to determine whether it provides the desired effect and to calculate the correct dosage. Then, several thousand patients are given the drug to determine its efficacy. The final stage includes ongoing monitoring throughout the medicine's lifespan. If the drugs are determined to be safe, they are granted a licence for use [2], [6].

Currently, the method used to research new drugs during the pre-discovery and discovery stages relies on a trial-and-error approach, in which a large number of molecules are tested until the best one is identified. Evaluating such a large number of potential drugs can be costly and very slow. AI techniques such as machine learning (ML) can be used to analyse a large number of molecules in a shorter space of time [3]. AI can observe patterns or trends not apparent to researchers. This can allow the correct molecule to be identified much more quickly than with the standard 5-stage approach, where researchers must first determine the correct drug target and then test a large number of molecules to find the best choice to treat the disease-causing area. Another use of AI in drug research is aiding in understanding how certain

chemicals interact with one another. This knowledge of drug interactions can allow researchers to recognise the adverse side effects that may result from mixing drugs. This can be useful for creating personalised treatment plans for patients with multiple diseases that require different medications to treat or manage [3].

An example of a company paving the way for AI use in the field is Recursion, which aims to create oncology drugs using AI. They established a partnership with a company specialising in AI-driven precision medicine. This collaboration allowed them to access a wide database of patient-centric oncology datasets, which they then combined with their own in vitro data to train AI models to find novel oncology biomarkers and targets. This AI model has enabled them to identify the novel drug target RBM39 and, consequently, produce a small-molecule targeting biomarker, REC-1245, which targets solid tumours and lymphoma [5]. Recursion has stated that the use of these AI models has allowed them to reduce the timeframe of drug testing to 18 months, compared to the usual 42 months it takes with standard testing. Another prominent example of AI models being used to assess molecules is their ability to identify a potential drug to treat advanced solid tumours: a cyclin-dependent kinase 7 inhibitor called REC-617. It is currently enlisting candidates for phase 1/2 of trials. There are currently no checkpoint inhibitors targeting kinase 7, and elevated levels have been suggested to increase the progression of cancer [5]. If this drug is successful, it could be a breakthrough in the treatment of certain cancers [4], [5].

Although the use of AI comes with many positive outcomes, it also has many limitations that must be considered.

One of the main issues lies within the training of the AI model. AI training requires a large amount of data. If this data is low quality or inconsistent, the model itself may not be reliable, leading to it providing incorrect information. There are also many ethical considerations, including biases and fairness. Bias can occur in AI models when the data used to train them underrepresents a certain demographic, or when the data is fragmented across silos. If the information used is biased, the resulting information produced may be inaccurate and unfair, which could lead to a poor estimate of the drug efficacy or dosage needed within certain groups. It is also vital to ensure that private data is kept secure. As AI systems rely on a large volume of data to train, this could lead to personal data being misused. As AI becomes more common in the drug discovery field, there is the potential for AI to be used to make decisions which may affect health and welfare, such as determining which drugs will be developed, assessing drug safety and calculating dosage. In order for AI to be successfully used in drug testing, it must be regulated and managed to ensure safety and address any ethical concerns [3], [7].

In conclusion, AI has proven its ability to transform the way drugs are tested and produced. It can work with researchers to test a large number of molecules and identify the best target for drugs to act on, drastically reducing the time to identify a target area for drugs to act on and helping to successfully find the corresponding drug to treat the disease. However, AI may also come with many issues that must be addressed. It cannot replace the current methods used during drug development, and should be used alongside human researchers, not instead of them.

By Mia Dibley

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Quantifying Social Attractiveness in Aesthetic Dentistry through Artificial Intelligence

Introduction

In the modern world, appearance strongly dictates how individuals are perceived [1], making aesthetic dentistry increasingly important. Although many patients attend dental appointments for clinical reasons, they expect aesthetic enhancement, even when it was not the initial reason for seeking treatment [2]. Traditional approaches to quantifying attractiveness have often relied on mathematical formulae, such as the Golden Proportion (0.62). This suggests an ideal width ratio for the maxillary lateral incisor relative to the central incisor to maximise facial harmony [2], [3], [4]. Social attractiveness is defined as the quality that triggers attraction or engagement within a specific community and is more subjective, reflected by peer perception compared to clinical mathematical ideals. However, these methods of quantification often prove inaccurate and do not guarantee that others will find an individual attractive. This is where artificial intelligence (AI) becomes particularly valuable, as it aims to quantify social attractiveness, meaning the ability to attract others in social settings [3].

Mechanism of AI Quantification

AI is categorised into four main areas: Machine Learning (ML), Natural Language Processing (NLP), Computer Vision (CV) and Artificial Neural Networks (ANNs) [5]. The foundation of many AI systems originates from ML, where mathematical models are trained using datasets to identify statistical patterns and generate predictions [4], [6]. An advanced branch of ML is Deep Learning (DL), which uses multi-layer neural networks, such as Convolutional Neural Networks (CNNs) [7], [8]. CNN architecture consists of an input layer, multiple hidden layers and an output layer. Within the hidden layers, convolutional kernels extract specific features from images. Pooling layers (POOLS) reduce feature map dimensions, ensuring the model ignores minor distortions [8], [20]. Activation functions, such as Rectified Linear Units (ReLU), allow the system to learn intricate non-linear tasks essential for diagnostic or aesthetic evaluations [8].

CNN models extract information from larger datasets, including facial images from the Internet Movie Database and Wikipedia.

One CNN model used multiple datasets from an online dating site containing over 13,000 facial images with more than 17

million ratings for attractiveness. Integration of such large datasets improves the model's accuracy when quantifying attractiveness.

To mirror clinical scenarios monochrome photos were utilised, allowing the algorithm to generate judgements based on societal perspectives rather than predetermined definitions of attractiveness. This enables AI to generate scores for both facial attractiveness and apparent age by analysing specific traits of the facial structure [3].

Clinical Applications of AI in Aesthetic Dentistry

Modern AI-based platforms such as SmileCloud and VisagiSMile utilise ML techniques to connect facial perception with specific anatomical features to generate personalised smile designs [6], [9], [10]. Another tool, Invisalign SmileView, employs 3D modelling to simulate treatment outcomes through digital simulations [4], [11], [12]. These simulations are modelled using photorealistic data captured through smiling selfies or standardised frontal photographs [11], [13]. In clinical settings, this is often improved by 3D models (STL and DICOM files) obtained from intraoral scanners [4]. The AI engine employs facial markers and orientation prompts to standardise image posture and lighting before comparing the information with a database of six million Invisalign cases to model how specific tooth movements will transform the patient's face [12]. This improves patient-clinician communication and guides patient expectations regarding clinical outcomes [9], [11], [12].

Digital simulations simplify clinical communication and increase patient attraction, yet they can be perceived as dangerous because clinicians remain responsible for verifying physical feasibility [9], [10], [11]. The potential health impacts are severe if clinical boundaries are ignored. Clinical evaluations illustrate that arch-width expansion should be limited to a maximum of two to three millimetres per quadrant to avoid risking gingival recession and bone

thinning. Furthermore, simulations may suggest interproximal reduction (IPR) beyond the 0.25 millimetre limit per side, which unnecessarily compromises the structural integrity of the tooth. Additionally, without human verification of root inclination relative to the bone, orthodontic movements can push roots into dense cortical bone or the maxillary sinus, causing significant bone remodelling and loss of periodontal support [4]. Poorly fitted prostheses can also lead to atrophy of the alveolar ridge and masticatory failure [6]; failure to transfer these projections in reality can cause patient distress [4], [11], [13].

Impact of AI on Dentofacial Outcomes

AI effectively determines treatment significance by assessing orthognathic treatment results on facial attractiveness and age appearance through pre- and post-treatment image analysis [3]. Algorithmic studies indicated enhanced patient attractiveness and aesthetics in 74.7% of cases and reduced their "apparent age", particularly following mandibular and bimaxillary procedures [3]. Similarly, in prosthodontics, studies show that a custom CNN model achieved 93.5% accuracy in a "pre-fabrication prediction" of the marginal fit of implants before they were processed [13].

Ethical Considerations of AI in Aesthetic Dentistry

Effectiveness of AI models relies on dataset quality used during the training phase of the algorithms, such as patient medical histories and various clinical scenarios [4], [14], [15]. There are also ethical considerations regarding patient privacy, especially since AI algorithms can be subject to biases that influence clinical decisions [16], [17], [18].

The technical reliance on data introduces ethical risks, as insufficiently representative datasets are the primary source of algorithmic bias [7], [16]. This occurs as AI algorithms are constrained by statistical distributions of training datasets. When

datasets contain imbalanced sample sizes, the algorithms may suppress the variations in information from minority groups to maintain mean trends and minimise loss functions. This is due to the lack of appropriate training to identify diversity among patients, leading to ineffective treatment, as some patient demographics are excluded [7].

In addition, the majority of DL models function as “black boxes”, providing results without showcasing a clear logical process. This understandably leads to scepticism

amongst practitioners who prefer to rely on experienced judgement [18], [19].

Conclusion

Ultimately, integrating AI into aesthetic dentistry acts as a powerful tool for communication, illustrating treatment results, plausibility and possible outcomes. AI serves as a guide for facial attractiveness, using its predictive nature combined with its ability to learn to augment aesthetic treatment, improving its success based on societal standards.

By Aditya Siva

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AI in the Worrisome War of Disease

Introduction

Disease can refer to a combination of signs and symptoms, phenomena associated with a disorder of function or structure or illness associated with a specific cause(s) [1]. A person can acquire a disease from infections, lifestyle choices, age, or their environment. They may also be born with diseases, such as genetic disorders or birth defects. Genetic disorders, which can present with birth defects, are caused by mutations, deletions, and additions in fetal DNA. Therefore, disease is separated into two main types: congenital and acquired.

With the use of artificial intelligence analysis both of these types of disease can either be prevented or identified early. This has impacted many fields of medicine, where AI has already changed or continues to change the way we treat, diagnose, and evaluate patients. For example, AI can aid research in finding a cure for diseases or assist in the creation of medical assistive devices such as new hearing aids. This gives patients some reassurance about their future, bringing some much-needed hope in a difficult period of their life. Ultimately, utilizing AI changes the field of medicine positively as it improves the management of disease, and brings optimism to patients and their families.

Dynamic Disease Detection Through AI

New advancements have allowed AI to observe protein patterns in blood. That gives it the capability to survey a patient's health for potential risks, such as specific protein changes that can signal the emergence of a potential disease in the

future [2].

Hence, AI is being used to recognize blood protein biomarkers associated with cardiac amyloidosis. Cardiac amyloidosis is a disease, where the protein amyloid builds up in the heart, making it too stiff to pump effectively [3]. The elevation of these protein biomarkers can show a likelihood for the disease in the future, up to 10 years early [4].

Remarkably, it is not just proteins that AI can analyze; a recently launched AI has the ability to perform liquid biopsies, in which DNA fragments in the blood are analyzed for disease. It is being used to capture epigenetic biomarkers to help determine if a patient is appropriate for a specific treatment [5]. Epigenetic biomarkers are indicators that show the impact of lifestyle and environmental choices on gene expression [6]. The impact of these factors on gene expression leads to changes in how genes operate, which can cause genes to turn on and off inappropriately. Subsequently, this leads to protein imbalances and reinforces the development of diseases such as diabetes.

In addition, epigenetic biomarker identification can give insights into the treatment outcome of colorectal cancer [7]. It is better known as bowel cancer, caused by unusual cell growth in the colon of the large intestine and rectum. The research into this invites more opportunities for AI intervention in cancer treatment, with the hope being that AI can learn to search for these specific biomarkers to help manage treatment plans in the future.

Lastly, on the topic of biomarkers, machine learning has been used to recognize biomarkers associated with neural tube defects [8]. These defects occur when the fetal brain or spine does not properly close; it is able to be predicted through the elevation of a specific protein in a prenatal blood test or through an amniotic fluid sample. Prenatal surgery can be conducted for some neural tube defects, improving the baby's quality of life in the future, but there is no definite cure.

However, with all the research conducted using AI, its capability to identify and evaluate factors of a disease is proven. This opens the pathway for more ground-breaking research studies that can possibly find a cure for neural tube defects.

Impacts on the Field of Genetics

Clinical geneticists have already used applications incorporated with artificial intelligence for years in diagnostics. They have and continue to assist geneticists by matching phenotypes of body parts such as parts of the face and bones to a range of genetic disorders [9]. Phenotypes are defined as the observable features of organisms or objects, which can include their behaviour and appearance. AI can analyse both phenotypical data and DNA. This can be observed through its inclusion in genetic tests such as karyotyping, chromosomal microarray, targeted panels, and whole exome sequencing. In some of these tests, it is used to detect changes in DNA using analytic software to uncover obscure mutations and their relation to disease [10].

In the instance of karyotyping, there is an exclusive focus on the integrity, structure, and number of chromosomes in a sample of cells. It is a lengthy and meticulous process. Consequently, to reduce the time taken for this, researchers have used AI in a creative manner. They have used it to aid in the creation of karyograms through image generation software [11]. Karyograms are images that display the appearance of all the chromosomes in a sample. Currently, human intervention is required to make the image usable after its generation, but it gives researchers more insight into the creative ways AI can be used to make research more efficient and straightforward.

A number of these genetic tests are done prenatally through invasive or non-invasive prenatal testing. Non-invasive prenatal testing uses a blood test from the mother to examine fetal DNA fragments, where AI scanning has improved prenatal detection of genetic disorders [12], [13].

Whereas, in invasive prenatal testing, genetic tests such as amniocentesis or chorionic villus sampling are used. During amniocentesis, a long, thin needle is inserted into the amniotic sac to obtain a sample of amniotic fluid. The fluid is then tested for genetic abnormalities with a 98% or 99% accurate diagnosis of chromosomal abnormalities [14]. Both amniocentesis and chorionic villus sampling are also able to find other inherited disorders [15], [16].

Notably, AI has already impacted prenatal care in patient prognosis. This is seen through its use alongside amniocentesis in a study to determine the birth outcomes of pregnant patients with short cervixes [17]. This predictive software may expand to other fields, allowing doctors to have a new perspective when creating a prognosis. Hence, the addition of AI in genetic tests has aided researchers with analysis and visualization, improving efficiency and thoroughness with a possible expansion of its prediction capabilities to other avenues of medicine.

The Future of Disease Eradication

AI has supported disease eradication by improving research itself. By correcting papers grammatically and structurally, it provides a way for researchers with problems in expression to push their work out. Furthermore, AI has streamlined research paper submission through automation, accelerating the awareness of critical research topics [18].

It is important to know every facet of these diseases such as its causes. This ties into the fact that an AI model has proven the ability to generate images of intricate proteins [19]. Using this skill, an entire database of protein images has been created, referred to as the AlphaFold Protein Structure Database. It allows a light to be shed on the protein's interactions with the human body and helps researchers uncover more details on its involvement in specific diseases.

Overall Message

AI is revolutionary. It has observed proteins

and DNA, signalling its potential to change medicine through protein observation and the capture of epigenetic biomarkers. Additionally, its capability in diagnostics involving genetic diseases has fundamentally changed the way genetic tests are conducted. Not only does it alter the way clinicians operate, but also alters

the way researchers write and submit. This is through the correction of grammatical errors in papers and the automation of research paper submission. Thus, it is clear that AI is becoming indispensable in medicine as a whole. With the ability to save and improve many lives, it is crucial that we support its continued growth.

By Teesha Cao

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Intersections in AI: Innovations, Risks, and Ethics

AI has emerged as a transformative invention with global impact, from automated vehicles to personalized healthcare [1]. It redefines technological boundaries and has resulted in improved utilisation of resources in the powerful fields of creativity, security, business, medicine, and education through AI's effective utilisation[1]. Artificial intelligence does not function independently, it shapes and is shaped by many domains.

Creativity

Creativity is often defined as “The use of imagination or original ideas to create something” [2]. However, whether AI can be said to possess creativity is dependent on their ability to form these ‘original ideas.’ Humans see, hear, feel, and learn which contribute in the making of their experiences and connections. Experiences further on result in the formation of ideas which finally demonstrate the act of creativity through human expression. In the case of AI, it involves machine learning that can learn a set of rules by studying a large amount of existing data and utilising this data to create new items or concepts based on a prompt [3]. For instance, if AI is prompted to generate text about the Sun, it is already provided with the information it needs to generate the mentioned text.

However, no matter how formidable an AI generated text might be, it does not consist of the humane process of forming opinions and memories. In simpler words, AI is not technically capable of having ideas and thoughts like individuals. Consequently, it can be concluded that AI generated content cannot be remarked as “creative” compared to human creations due to the beliefs, and ideas of humans which make them differ. This is because AI may know that the sun gives off heat and makes it possible for light to exist but it does not have its own personal thoughts, feelings, and memories in the same way that humans do.

Security

Cyber threats have with time become more sophisticated, resulting in a need for more intricate technologies in order to replace the outdated traditional security measures. This is because the previously used security systems lack current capability standards of real-time monitoring and automated response capabilities. Cyber criminals have started using AI to attack and infiltrate enterprise security measures. Through threat detection and prevention, AI offers a defense against these new threats of increased ransomware which encrypts data and demands payment for return, as well as malware infections which compromise systems or steal data [4]. AI in cybersecurity analyzes large datasets at speeds unachievable for humans, which strengthens not only detection of threats, but response towards them as well [4]. However, while AI systems are efficient, they can make mistakes which causes concern for users. These mistakes and loopholes include unreliable AI systems with rarely transparent decision-making procedures [5]. Moreover, their actions and alerts are unpredictable as well [5]. Decision-makers worry that AI could miss a threat or report a false one, which leads to hesitation in relying on AI systems for essential security decisions. The training of AI systems through biased datasets may also cause unfair targeting or threat assessments [5].

Business

The use of AI initially began through chatbots and customer help care automation. But the observation of a 25% increase in customer satisfaction resulted in the belief that reducing AI to a simple FAQ chatbot misses the full scope of its potential [6]. The use of AI later on expanded in the sectors of 24/7 customer service, sales acceleration, and enhancing user engagement through marketing which included AI assistance and quick and efficient solutions of internal inquiries. While it is unlikely to replace humans entirely in the near future, AI is already transforming how businesses operate. Quite often, clients require developing their own large language models in order to maintain a unique personal identity, something which is still left to be mastered [6]. Businesses need to navigate ethical challenges such as bias, privacy, transparency, and accountability when adopting AI [6].

Healthcare

As data volume and complexity increase, AI can help healthcare affair teams harness insights faster, more effectively, and in ways that reveal deeper trends and topic shifts over time [7]. However, successful AI integration requires careful planning, resource allocation, and an understanding of both pre- and post-implementation requirements. Thus, the usage of AI in healthcare has been divided into the stages of understanding the potential benefits and limitations of AI; and identifying critical pre- and post-implementation needs [8]. The requirement for ongoing human involvement, strict validation of sources, and constant feedback mechanisms highlight current deficiencies in integration, responsibility, and flexibility of AI healthcare. Thus, although it presents considerable promise, successful deployment of AI relies on enhancing the connections among AI systems and humans in decision-making, data quality standards, ethical governance, and organizational processes indicating that AI in healthcare is not a standalone technology [8].

Furthermore, limited resources affect AI adoption and implementation. The efficiency of AI depends mainly on high-quality data, which is challenging to acquire and verify. Moreover, submitting this data can be risk-prone as it involves revealing sensitive information regarding the patients.

Education

AI is changing the educational domain and is bringing about noticeable improvements in academical sectors along with challenges. Advanced technologies powered by artificial intelligence such as teaching systems, chat bots, and other advanced tools for making images or videos show how AI has influenced classrooms all over the globe. These technologies offer personalised feedback and adaptive learning [9]. AI in education consists of the improvement of AI-based tools as well as its use to understand and improve learning. While its benefits in education are numerous, there are also concerns and challenges that require consideration. AI algorithms may accidentally exhibit bias, leading to a disadvantage for students from vulnerable groups. The data collection necessary for AI-driven educational tools raises concerns about privacy and misuse of sensitive student information [9]. There also exists a risk that educators and students may become overly dependent on AI technologies, which could lead to lessened critical thinking skills [9]. AI in education also raises the issue of unequal access to technology, widening the digital divide.

Conclusion

The growing capabilities of artificial intelligence and its rising use across worldwide industries have heightened the demand for focused attention on the latter part of this matter. With AI systems rapidly spreading across social, economic, and cultural frameworks, lack of adequate regulations pose various risks. These include job displacement, biases and discriminatory actions, loss of personal

privacy, the spread of false information, increased security risks, environmental degradation, and the concentration of power in the hands of few. Tackling these

issues is crucial in order to guarantee that the development and implementation of AI stay in line with the personal interests of people.

By Angel Batra

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The Ultimate Tech Quest: How AI Transform Computer Science

Introduction

In recent decades, artificial intelligence (AI) has often been portrayed in extreme or alarmist terms, sometimes suggesting catastrophic consequences for society or the planet. Claims such as “AI will destroy our planet” are unfounded but appear frequently in public discourse and that tend to obscure a more productive discussion about what AI actually is and how it contributes to computer science. A necessary first step is to refute these claims by clearly defining artificial intelligence. To do that it is important to provide a precise and unambiguous definition, since the concept of AI is often subject to interpretation and misunderstanding.

Defining Artificial Intelligence

Artificial intelligence is a field within computer science that studies the theoretical foundations, methodologies, and techniques used to design hardware and software systems capable of goal-directed behavior, learning, and adaptive decision-making. These systems may exhibit capabilities that appear, to an external observer, characteristic of human intelligence [1]. In addition, AI has been influenced by numerous fields, including mathematics, philosophy, economics,

linguistics, computer science and more.

AI and Computer Science

Artificial intelligence occupies a distinct position in computer science, interacting with it at both theoretical and applied levels. At a theoretical level, AI tends to research and develop basic theories, both existing ones (e.g. mathematical, logic) and entirely new ones. One example is problem theory that focuses on formally defining what a “problem” is, how problems can be represented, and how solutions can be systematically searched for or generated. In AI, a problem is often modeled as:

- 1) An initial state
- 2) A set of possible action
- 3) A state space describing all reachable configurations
- 4) A goal condition

This abstraction allows AI systems to treat diverse tasks such as pathfinding, game playing, planning, or puzzle solving within a single theoretical framework. Search algorithms (e.g., breadth-first search, heuristic search) and complexity analysis emerge directly from this theory. More broadly, AI theory investigates questions such as: what does it mean for a system to reason, learn or act intelligently and how can knowledge be represented in a way that is both expressive and computable.

In the field of computer science applications, AI serves as an experimental area aimed at extending applications, especially non-numerical ones. Although modern AI does not require physical embodiment, its principles are often applied in robotics, where intelligent systems interact with the physical world. The relationship between computer science and robotics can be examined more clearly by comparing their roles. Computer science focuses on the design and behavior of computational systems, while robotics applies these systems to machines capable of sensing and acting in the physical

environment. From an abstract perspective, this interaction can be modeled as three entities: humans, the world, and machines, as illustrated in the tripolar diagram of reality.

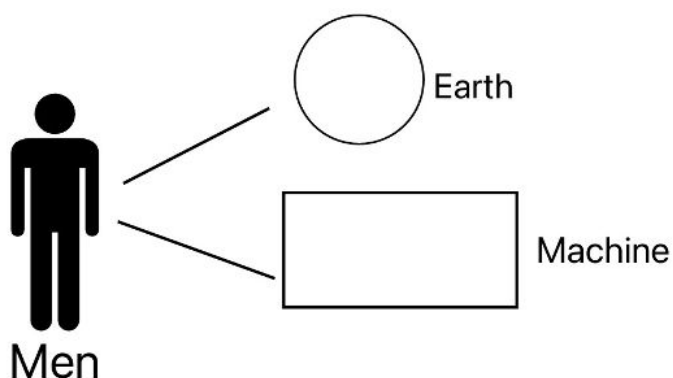


Figure 1 - Tripolar diagram of reality

Problems, Algorithms and Representation

With computer science, man conceives the creation of a machine, the computer, which roughly reproduces certain faculties of human intelligence that reflect on reality and solves some of the problems caused by such reflection. In this sense, computers can perform forms of abstract reasoning without direct interaction with the physical world. Robotics extends this idea by embedding computational systems within machines that can sense and act in the physical environment, combining reasoning with perception and action. As a result, robots can perform limited forms of understanding and interaction that would otherwise require direct human involvement. Studying and highlighting the various ways in which it can be modeled. The activity of modeling a problem is called, in AI, problem representation or knowledge representation. Within this framework, automatic problem solving became a central research focus. Automatic problem solving refers to methods that enable a system to generate solution procedures autonomously or interactively, rather than executing only prewritten algorithms. Historically, this approach emphasized algorithms that generate other algorithms, although modern AI more often frames this capability in terms of learned models. In AI literature, these higher-level procedures

problem that the machine is asked to solve automatically. With automatic problem solving, the machine is conceived as having the ability not only to be skilled and fast in executing algorithms constructed by humans, but also to autonomously construct the algorithms necessary to solve problems [2]. These algorithms, constructed by the machine, may be executed either autonomously or used by humans as decision-support tools. To analyze problem solving conceptually, it is useful to consider how a machine internally represents and evaluates possible solutions. After all, every problem, from making a move in chess to recognizing a face, can be seen as a path to be followed where you start from an initial situation and have to reach a goal. AI therefore, tries to construct a mental map made up of possible steps, just as a person would do when he has to make a difficult decision. To understand how AI reshapes computer science, it helps to look at the different ways machines can approach a problem. Early AI research showed that a machine could reason by exploring possibilities step by step, much like a person navigating an unfamiliar city. This idea that problem solving can be viewed as a search through a space of possible states was central in early foundational work in AI and helped define how computers could behave intelligently even with limited information [3]. A second major approach emerged with symbolic AI.. Here, instead of exploring paths, the machine reasons using structured knowledge: facts, rules, and logical relations. Symbolic AI showed that intelligent behavior could arise from the manipulation of structured knowledge, influencing early expert systems early expert system and shaped the way computer scientists thought about representing complex information [4]. More often called meta-algorithms or inferential algorithms operate on representations rather than raw data. The use of such inferential algorithms consists at providing, as input data, the representation of the recently machine learning and neural networks introduced a third perspective.

Rather than relying on explicit instructions, learning-based systems infer patterns directly from data. Some patterns in tasks like image recognition or translation are too complex or detailed for humans to write rules for. Images: AI notices tiny combinations of shapes, textures, lighting, and colors that humans can't describe fully. Translation: AI picks up context-dependent word meanings, idioms, and grammar nuances that are hard to spell out manually. In short, AI can learn subtle patterns automatically from data that humans can't easily explain or codify, making it possible for AI systems to master tasks such as image recognition, speech understanding, and translation. Modern deep learning research showed that learning-based systems could scale to extraordinary levels of performance when trained on large datasets [5]. When search, symbolic reasoning, and learning are considered together, their combined impact on computer science becomes clear. As Marco Somalvico (1941–2002) that was an Italian pioneer in artificial intelligence (AI) and robotics. He was a professor at the Politecnico di Milano and founded the AI & Robotics Lab (AIRLab).

He explored not just technical AI, but also the conceptual, ethical, and cultural implications of AI. He studied intelligence, learning, and the relationship between humans and machines. emphasized in his work, AI changes not only the tools available in computing but also the way people conceptualize problems themselves. Instead of programming precise procedures for every task, people design systems that can construct or adapt their own procedures when needed [6]. This pushes computer science beyond traditional computation and into new territories: modeling knowledge, handling uncertainty, learning from data, and even interacting with the physical world through robotics. In this sense, AI acts as both a driver and a mirror for computer science. It expands what computers can do, while also forcing us to rethink ideas such as “algorithm,” “information,” and “intelligence.” As AI grows, it continues to draw from many other branches psychology, linguistics, neuroscience, mathematics, showing that intelligence is not just a computational concept, but a profoundly interdisciplinary one.

By Vanessa Apuzzo

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Thank You!

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Alison Barth	Maxwell H. & Gloria C. Connan Professor in the Life Sciences, Carnegie Mellon University
Dan Congreve	Assistant Professor of Electrical Engineering, Stanford University
Tim Coulson	Professor of Zoology, University of Oxford
Steven Cundiff	Harrison M. Randall Collegiate Prof. of Physics & Prof. of Electrical Engineering and CS, University of Michigan
Kris Gunsalus	Professor of Biology, New York University
Sonia Katyal	Roger J. Traynor Distinguished Professor of Law, UC Berkeley
Raymond Mooney	Professor of Computer Science, University of Texas at Austin
Nilay Shah	Professor of Process System Engineering, Imperial College London

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