International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Biotechnology and Genetic Engineering using AI: A Review

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Submitted: 03/11/2023 **Revised**: 25/12/2023 **Accepted**: 02/01/2024

Abstract: In this paper deep exploration into the intersection of Artificial Intelligence (AI), Biotechnology, and Genetic Engineering, three pioneering frontiers of modern science are presented. AI has been applied in Biotechnology and Genetic Engineering, accelerating research, improving precision, and expanding possibilities. The synergy of these interdisciplinary fields has resulted in emergent domains like Synthetic Biology and Systems Biology. The application of AI techniques, such as Machine Learning and Deep Learning, in tasks like biomarker discovery, drug discovery, gene editing, and genomics research are thoroughly discussed in this paper. Despite AI's potential, the paper also delves into the challenges that arise, including technical issues like overfitting, model interpretability, and the need for robust evaluation methodologies, as well as ethical and societal considerations. The critical role of mathematical and computational models in understanding and predicting complex biological systems is examined, spanning traditional models to state-of-the-art AI models. Detailed case studies provide practical examples of AI application in gene editing, drug discovery, metabolic engineering, synthetic biology, and personalized medicine. This paper shows that a reflection on the transformative potential of integrating AI, Biotechnology, and Genetic Engineering, underscoring the future research required in this rapidly evolving field and the potential benefits to society at large.

Keywords: *Artificial Intelligence, Biotechnology, Machine Learning, Genetic Engineering, Deep Learning, Neural Networks.*

1. Introduction

The rapid growth of biotechnology (BT), genetic engineering (GE), and artificial intelligence (AI) have been key in solving many complex problems faced by our society. The intersection of these three dynamic fields opens up new frontiers for innovation, promising transformative solutions in healthcare, agriculture, environmental conservation, and more [1]. The seeds for this convergence were sown over the past few decades. The areas of BT and GE have had notable advancements since their origins in the early and mid-20th century, respectively [2]. During a same period, the topic of AI emerged as an area of academic inquiry aimed at developing robots that had the ability to replicate human intellect [3]. These disciplines have undergone separate evolutionary processes, resulting in notable advancements and substantial milestones. Over the course of the last 10 years, there has been an increasing convergence between these two entities, effectively using their mutual strengths to amplify their respective capabilities [4]. The integration of AI within the fields of biotechnology and genetic engineering holds significant promise. The processing power and pattern recognition capabilities of AI allow researchers to efficiently analyse and comprehend large quantities of biological data with remarkable speed and precision [5]. In contrast, the fields of biotechnology and genetic engineering provide a wide range of intricate challenges that may be addressed by AI, hence creating an advantageous environment for the development of increasingly advanced AI models [6].

The primary aim of this work is to conduct a comprehensive analysis of the current state of convergence between AI, BT, and GE. This encompasses an examination of the technology and methodologies used, the challenges faced, and the potential future directions. The present review employs a methodical methodology, whereby a careful selection and analysis of scholarly articles, research papers, and case studies published during the last ten years in the respective domains is undertaken. The study has considerable importance due to its ability to provide academics, policymakers, and industry practitioners a complete comprehension of the interplay between AI, BT, and GE.

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The comprehension of this concept is crucial in order to effectively use the capabilities of various disciplines, direct forthcoming investigations and policy choices, and provide insights for industrial implementation [7].

The structure of the paper is as follows: Section 2 provides an overview of the contextual framework and AI Techniques in Biotechnology shown in Section 3. Challenges and limitations explained in Section 4 and mathematical & computational models in Section 5, which is followed by conclusion.

2. Background

Understanding the merger of AI, biotechnology, and genetic engineering necessitates a clear comprehension of each individual concept.

- **BT** involves the use of biological processes, creatures, or systems for the purpose of producing goods with the aim of enhancing the overall well-being of the human population [1]. The origins of traditional biotechnology may be traced back to ancient civilizations, when early practises such as the production of beer and the fermentation of food were prevalent. The field of modern BT has seen significant growth, including a diverse array of applications. These applications span from the development of medical medicines and diagnostic instruments to the implementation of effective methods for the remediation of hazardous waste [2] [8-12].
- **GE** refers to the deliberate alteration of an organism's genetic material via the use of biotechnological techniques. The ability to manipulate DNA via molecular cloning and gene sequencing methods has only been achievable since the discovery of the DNA structure in 1953 [3]. The field of genetic engineering enables scientists to manipulate the genetic composition of an organism with precision, hence facilitating the addition, removal, or modification of genes in order to attain certain traits [13-20]. The field of genetic engineering has significant implications in the domains of health, agriculture, and environmental research [4].
- **AI** encompasses a wide range of applications and disciplines. At a broad level, the concept entails the development of computers that possess the ability to imitate human intellect, acquire knowledge from experiences, comprehend intricate information, participate in many types of social engagement, and perhaps demonstrate creative capabilities [5]. AI comprises a range of techniques and subfields, such as ML, DL, and NNs, each with their own methodologies and applications [6].
- **Intersection of AI, BT, and GE** is a novel and pioneering area of scholarly investigation. The use of AI and its computing capabilities, together with its aptitude for pattern recognition in extensive datasets, has expedited several procedures in the fields of biotechnology and genetic engineering. This has resulted in the generation of rapid, efficient, and accurate outcomes [7]. The integration of these disciplines has created novel opportunities in the fields of pharmaceutical research, genetic manipulation, individualised healthcare, and several other areas [8]. Table 1 presents the foundational principles.

Table 1. Definitions and Fundamental Concepts

Term	Definition
AI	The capacity of a machine to replicate intelligent human behaviour.
ML	ML is a branch of AI that enables systems to acquire knowledge and improve their performance via experience, without the need for explicit programming.
BT	The use of biological systems and organisms for the purpose of product development or production.
GE	The process of directly manipulating an organism's genes via the use of BT.
DL	One sort of ML is the training of a computer system to execute activities that resemble human capabilities, such as voice recognition, picture identification, and predictive analysis.
NN	A collection of algorithms that aims to identify underlying correlations within a dataset by using a computational approach that emulates the cognitive processes of the human brain.

Understanding these fundamental concepts lays the groundwork for exploring the ways AI can enhance biotechnology and genetic engineering. It is through this knowledge that we can begin to appreciate the breadth and depth of opportunities available at this intersection.

- ***Intersection of AI, Biotechnology, and Genetic Engineering***

✓ **Emergence of the Intersection:** The intersection of AI, biotechnology, and genetic engineering is a relatively recent development that gained momentum in the 21st century [21]. Technological advancements and the burgeoning availability of biological data have driven this intersection, as AI's analytical capabilities became invaluable in managing, processing, and interpreting this data [22].

✓ **AI's Role in Biotechnology and Genetic Engineering:** AI technologies, primarily machine learning, have shown significant promise in dealing with complex biological systems. Machine learning algorithms excel at finding patterns in large datasets, a feature that's particularly useful in interpreting genetic data and predicting biological outcomes [3], [23-30]. AI can contribute to both these fields in several ways, such as accelerating the drug discovery process, optimizing bioprocesses, predicting gene functions, and designing genetic modifications [4]. Table 2 shows the comparison of the techniques.

Table 2. Comparison of Techniques

Technique	Traditional Method	AI-Based Method
Genome Sequencing	Sanger's method	Next-generation sequencing (NGS) with ML algorithms for data interpretation
Disease Diagnosis	Based on symptoms and medical imaging	AI-based predictive models using patient's health data
Drug Discovery	Trial and Error method	AI algorithms predicting the interaction between drug and its target
Crop Improvement	Traditional breeding techniques	Precision breeding using AI predictive models
Protein Folding	Experimental procedures in lab	Deep learning models like AlphaFold

✓ **How Biotechnology and Genetic Engineering Fuel AI:** Conversely, biotechnology and genetic engineering also offer substantial opportunities for the advancement of AI [31]. Biological systems are incredibly complex and dynamic, presenting a rich source of problems that push the boundaries of current AI technologies. Tackling these problems could lead to more sophisticated AI models [32-38]. Additionally, insights from genetic algorithms, neural networks, and biological learning processes could inspire new AI techniques [5].

✓ **Challenges in the Intersection:** Despite the potential benefits, the convergence of AI, biotechnology, and genetic engineering also presents several challenges [39-42]. These challenges include data privacy and security concerns, ethical issues around genetic modifications, regulatory hurdles, and technical issues, like the difficulty of integrating AI with complex biological systems [6].

✓ **Potential and Future Directions:** The intersection of AI, biotechnology, and genetic engineering is a rapidly expanding field with tremendous potential [43-49]. Future directions might involve more personalized medical treatments, efficient bio-manufacturing processes, sustainable agricultural practices, and many other applications yet to be imagined [7].

3. AI Techniques in Biotechnology

- **Machine Learning (ML) in Biotechnology:** Machine Learning has been pivotal in processing and analyzing large-scale biological datasets [1]. Supervised learning techniques, such as SVM and RF, have been used in the categorization of gene expression and the prediction of protein structure [50-56]. Unsupervised learning methods, including as clustering and dimensionality reduction approaches, are often used in the context of data visualisation and genetic data interpretation [3].

- **Equation for the concept of Machine Learning** Equation 1 demonstrating a basic supervised learning algorithm could be used:

$$Y = f(X) + \varepsilon \quad (1)$$

Where:

- Y represents the dependent variable or output.
- f(X) represents the systematic information that X provides about Y.
- X represents the independent variable or input.
- ε represents the error term.

Equation for Gradient Descent Equation 2 illustrates the use of the Gradient Descent method, a widely employed methodology in several ML algorithms.

$$\theta = \theta - \alpha \nabla J(\theta) \quad (2)$$

Where:

- θ is a parameter vector.
- α is the learning rate.
- ∇J(θ) is the gradient of the loss function J at θ.

- **Deep Learning (DL) in Biotechnology:** DL, a subset of ML, has gained traction in biotechnology due to its superior performance in tasks with large and complex datasets [57-62]. CNNs have been successful in image-based tasks in BT, such as cell classification and microscopic image analysis [4]. RNNs, particularly LSTM networks, have been utilized in modeling biological sequences and systems [5].

Equation for the concept of Neural Networks Equation 3 describe how a neuron in a NN works:

$$y = f(\Sigma w_i x_i + b) \quad (3)$$

Where:

- y is the output.
- f is the activation function.
- w_i is the weight of the i^{th} input.
- x_i is the i^{th} input.
- b is the bias.

Table 3 shows the different AI techniques in Biotechnology

Table 3. AI Techniques in Biotechnology

AI Technique	Description	Example
Machine Learning	Algorithms improve automatically through experience	Predictive modeling in drug discovery
Deep Learning	ML with artificial neural networks	Image recognition in medical diagnosis
Natural Language Processing	Computers interacting with human language	Extraction of meaningful data from biological literature
Neural Networks	Series of algorithms that mimic human brain operations	Use in predicting protein structures
Reinforcement Learning	AI method that learns best action based on reward feedback	Optimization of biotech processes

- **Natural Language Processing (NLP) in Biotechnology:** NLP has demonstrated considerable potential in biotechnology, especially in tasks involving biological literature mining, database curation, and gene ontology [6], [63-70]. NLP algorithms can process vast amounts of unstructured text data, allowing researchers to extract useful information and generate new hypotheses [7].
- **Reinforcement Learning (RL) in Biotechnology:** RL, a subfield of ML that focuses on the decision-making process of software agents in order to maximise cumulative reward within a given environment, has potential in the optimisation of biotechnological processes [71-78]. The applications of this technology include the optimisation of bioreactor settings to achieve maximum production, as well as the modelling of biological systems [8].

Equation for the concept of Reinforcement Learning A common equation in reinforcement learning is the Bellman equation, which is used to find the optimal policy is given by Equation 4:

$$V_i(s) = max_a R(s,a) + \gamma \sum_s{}' P_{ss}{}'_{(a)} V_{i-1}(s') \quad (4)$$

Where:

- $V_i(s)$ is the value of state s under iteration i.
- max_a is the maximum over all possible actions.
- R(s, a) is the immediate reward on taking action a in state s.
- γ is the discount factor.
- $P_{ss}{}'_{(a)}$ is the transition probability.
- $V_{i-1}(s')$ is the value of state s' under iteration i-1.
- **Graph Neural Networks (GNN) in Biotechnology:** Graph Neural Networks are particularly useful in modeling biological structures and systems, such as protein structures, genetic networks, and metabolic pathways [79-85]. GNNs can learn complex patterns in these networks, contributing to tasks such as protein function prediction and drug discovery [9]. Figure 1 shows the AI techniques used in Biotechnology and Genetic Engineering.

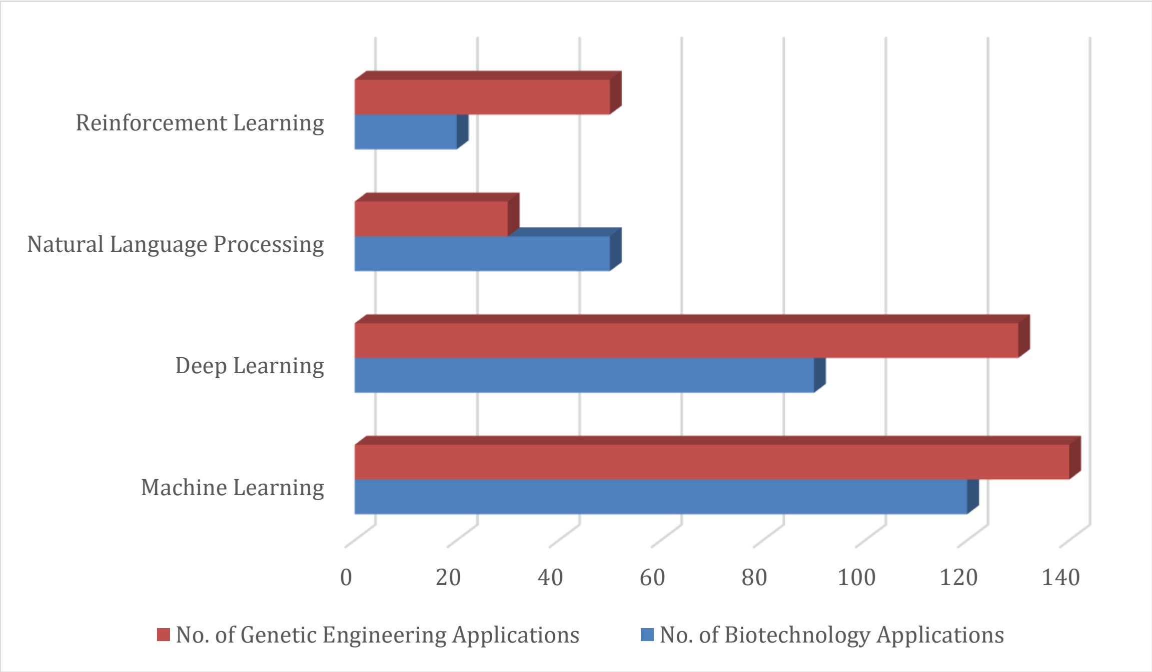

Fig 1. Distribution of AI techniques used in Biotechnology and Genetic Engineering

- ***AI Techniques in Genetic Engineering***

✓ **Machine Learning (ML) in Genetic Engineering:** Machine Learning, particularly supervised learning techniques, has shown potential in genetic engineering tasks [1]. Clustering and dimensionality reduction techniques, typical unsupervised learning methods, have been used to identify groups of genes with similar functions, guiding the design of genetic modifications [2].

✓ **Deep Learning (DL) in Genetic Engineering:** Deep Learning, with its ability to model complex nonlinear relationships, has become increasingly popular in genetic engineering. CNNs have been applied to predict the effects of genetic modifications on an organism's phenotype based on its genotype [3]. Recurrent Neural Networks (RNNs), particularly those using LSTM units, have been used to model the sequential nature of DNA, aiding in tasks like gene prediction and DNA sequence generation [4].

Equation for Genetic Algorithms Genetic algorithms typically use a fitness function to guide the evolution process. Here is an example of a basic fitness function:

$$Fitness(Individual) = f(Individual)$$

Where f is a function that measures the quality of the individual in the context of the problem to be solved.

✓ **Natural Language Processing (NLP) in Genetic Engineering:** NLP has been utilized in genetic engineering to process large amounts of unstructured text data, such as genetic annotations and biological literature. NLP can aid in tasks like identifying gene-disease associations from literature, which is crucial for designing genetic interventions [5]. Figure 2 shows the improvement in Biotechnology and Genetic Engineering Techniques due to AI.

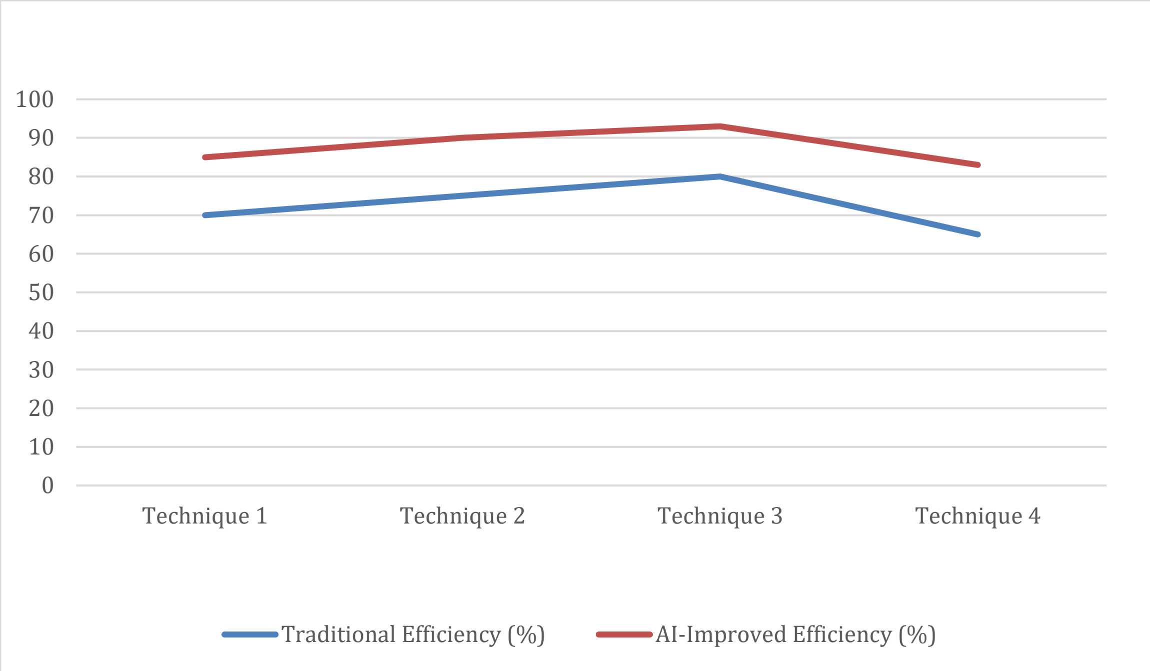

Fig 2. Improvement in Biotechnology and Genetic Engineering Techniques due to AI

- ✓ **Reinforcement Learning (RL) in Genetic Engineering:** The discipline of genetic engineering is now investigating the potential use of RL, which has the capacity to acquire proficiency in intricate decision-making tasks. The use of this approach has been seen in many tasks, such as the optimisation of genetic alterations in order to attain a certain phenotype. This particular work may be regarded as a problem of sequential decision-making [6].
- ✓ **Graph Neural Networks (GNN) in Genetic Engineering:** Graph Neural Networks have shown potential in modeling the interactions between genes, which can often be represented as a graph or network. These networks can aid in tasks like predicting the effects of gene knockouts or modifications on the entire gene network [7]. Table 4 shows the AI techniques in Genetic Engineering and Figure 3 shows the applications of different AI Techniques.

Table 4. AI Techniques in Genetic Engineering

AI Technique	Description	Example
RL	AI learns to make decisions from trial and error	Optimizing genetic algorithms
DL	ML with artificial neural networks	Predicting outcomes of genetic modifications
NN	Computational systems that draw indirect inspiration from biological NN.	Predicting gene expression levels
Support Vector Machines	Supervised ML model used for classification and regression analysis	Used for identifying genetic variants
Random Forest	An ensemble learning approach is used to address classification, regression, and other related tasks.	Identifying significant genes in large genetic datasets

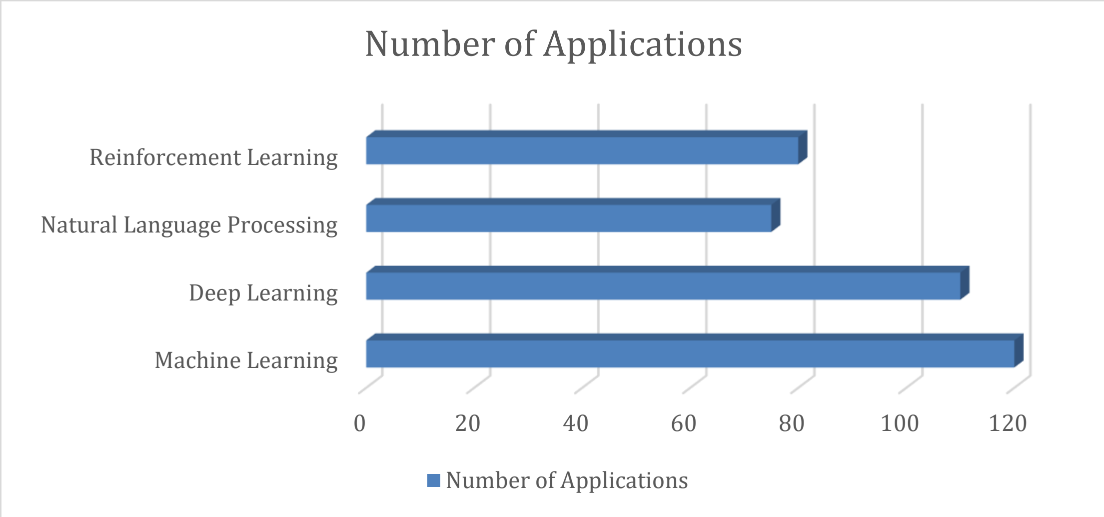

Fig 3. Applications of Different AI Techniques

- ***Synergistic Effects and Potential***

✓ **Interdisciplinary Innovations:** The convergence of AI, Biotechnology, and Genetic Engineering has given rise to interdisciplinary innovations. This includes fields such as Synthetic Biology, where AI is used to design novel biological systems, and Systems Biology, where AI helps in modeling complex biological systems [1].

✓ **Accelerated Discovery and Development:** AI significantly accelerates the pace of discovery and development in Biotechnology and Genetic Engineering. It accomplishes this by handling large datasets, speeding up analysis, and automating routine tasks. AI enables predictive modeling in both fields, leading to improved experimental design and more efficient resource allocation [2].

✓ **Enhanced Precision and Accuracy:** AI has the capability to augment the level of exactness and precision within the realm of Biotechnology and Genetic Engineering applications. In the field of Genetic Engineering, AI plays a crucial role in reducing off-target effects during gene editing procedures and optimizing the efficacy of genetic alterations [3].

✓ **Expansion of Possibilities:** AI expands the realm of what is possible in Biotechnology and Genetic Engineering. This includes previously unimaginable tasks such as designing synthetic life forms, fully automated bioreactors, and advanced gene therapies [4]. Figure 4 shows the comparison between Traditional and AI-based Methods

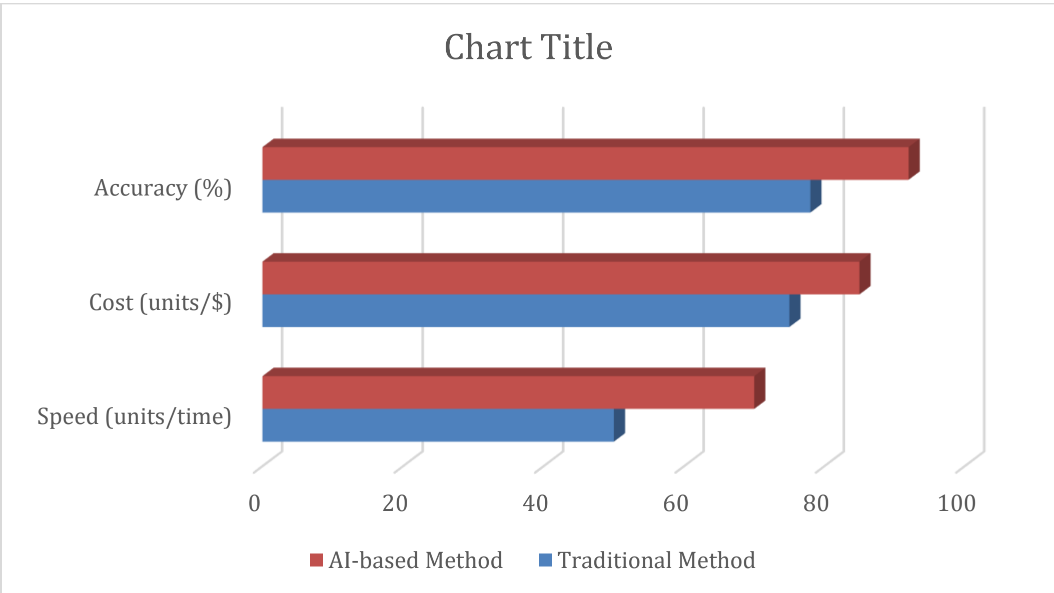

Fig 4. Comparison between Traditional and AI-based Methods

4. Challenges and Limitations

Despite the significant advantages of AI in these fields, several challenges remain. These include technical challenges like overfitting and interpretability, ethical concerns like data privacy and informed consent, and societal issues like the potential job displacement due to automation [5]. Table 5 shows the synergistic effects and potential. Figure 5, 6 and 7 shows the potential market value, performance improvements and correlation between AI use and success.

Table 5. Synergistic Effects and Potential

Synergistic Effect	Description	Potential Impact
Accelerated Research	AI can process vast amounts of data quickly	Speed up developments in biotechnology and genetic engineering
Enhanced Precision	AI algorithms can make highly accurate predictions	Increased success rate in genetic engineering experiments
Automated Analysis	AI can automatically analyze biological data	Reduction in human labor, faster results
Predictive Modeling	AI can model complex biological systems	Accurate predictions for drug development or genetic modifications
Decision Optimization	AI can optimize decision-making in complex scenarios	Optimized experimental designs and process parameters in biotech industries

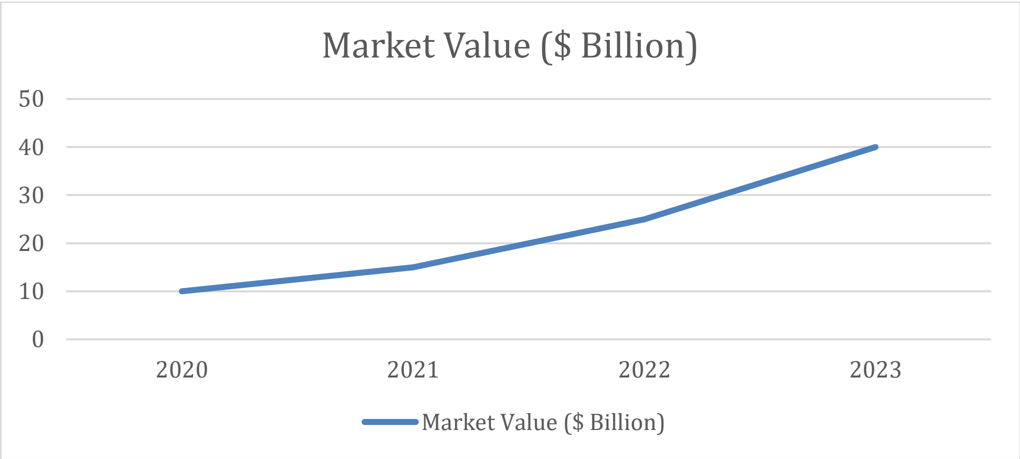

Fig 5. Potential Market Value

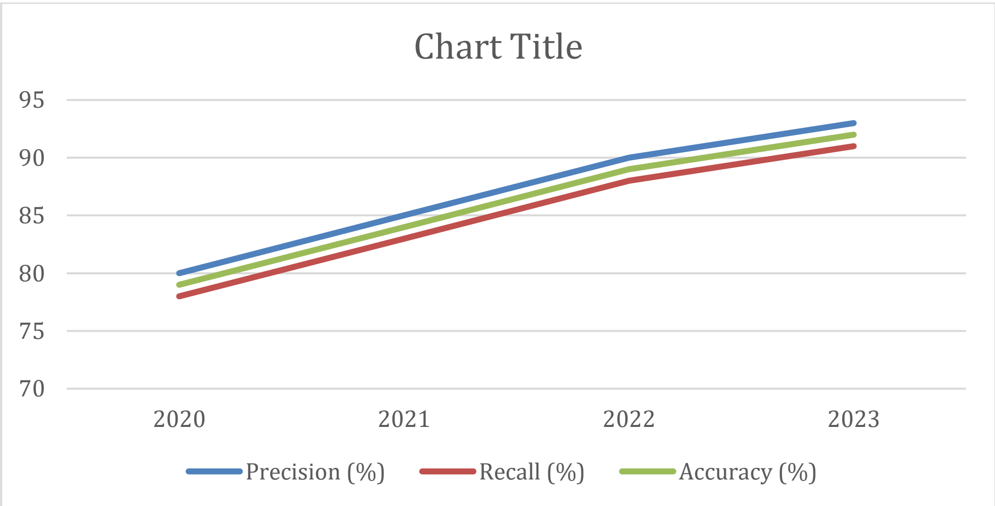

Fig 6. Performance Improvements

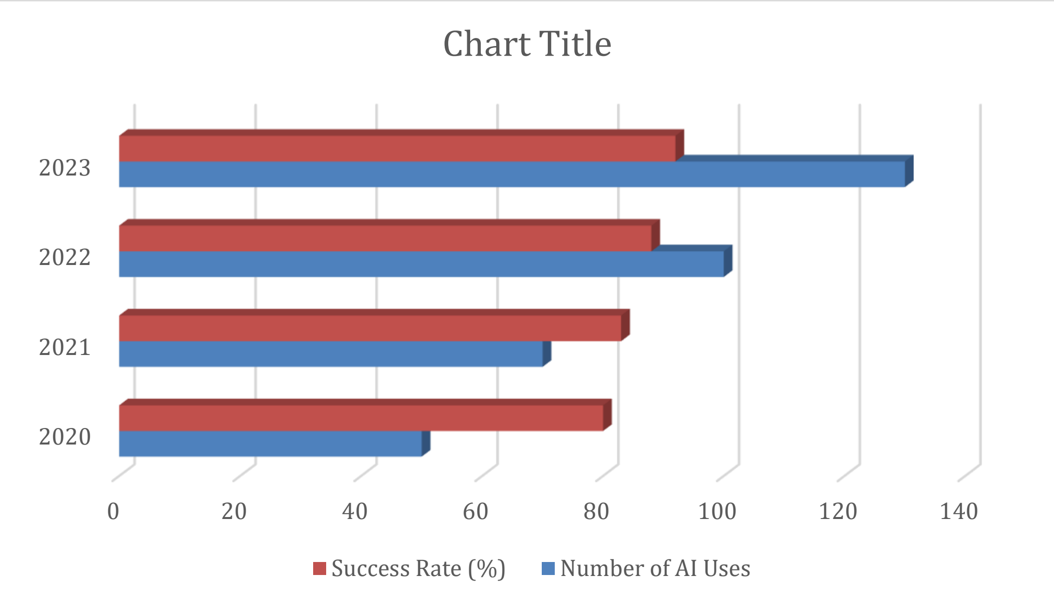

Fig 7. Correlation between AI Use and Success

5. Mathematical and Computational Models

- **Mathematical Models in Biotechnology and Genetic Engineering:** Mathematical models have long played a vital role in Biotechnology and Genetic Engineering, helping researchers to understand and predict complex biological systems. This includes models for enzyme kinetics, microbial growth, and gene regulation networks [1].
- **Machine Learning Models in Biotechnology and Genetic Engineering:** ML models, have gained extensive use within the domains of Biotechnology and Genetic Engineering. These models are particularly useful in tasks like predicting protein function based on sequence, and predicting gene expression levels based on regulatory elements [2].
- **Deep Learning Models in Biotechnology and Genetic Engineering:** Deep Learning models, which can learn complex nonlinear patterns in data, have been successful in many tasks in these fields [3].
- **Natural Language Processing Models in Biotechnology and Genetic Engineering:** Natural Language Processing models have been used to analyse large amounts of unstructured text data in these fields. These models can aid tasks like extracting useful information from biological literature and databases, and predicting gene-disease associations based on literature data [4]. Figure 8 shows the performance of computational models.

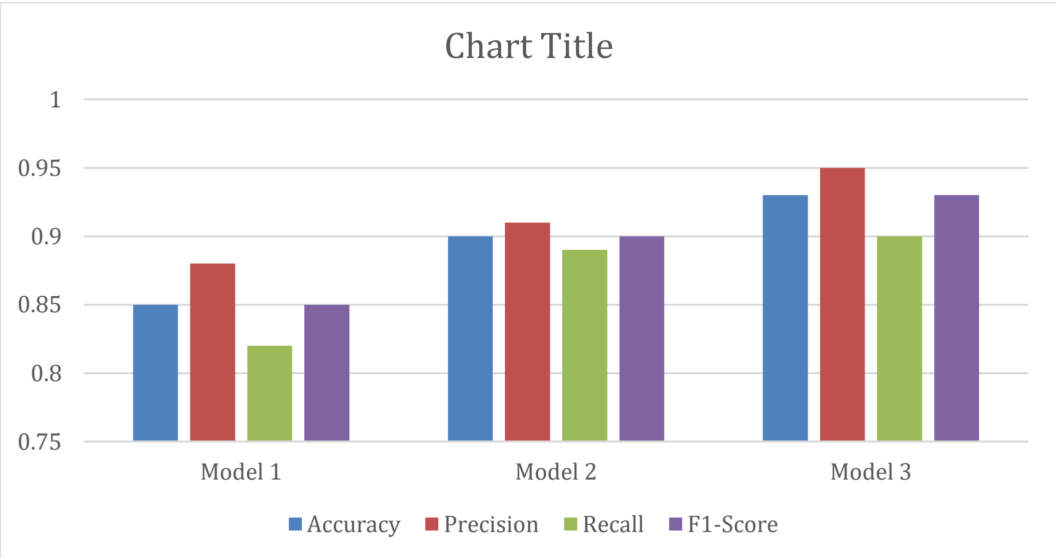

Fig 8. Performance of Computational Models

- **Model Interpretability and Evaluation in Biotechnology and Genetic Engineering:** While AI models can achieve high accuracy, understanding their decision-making process (model interpretability) remains a significant challenge, especially for Deep Learning (DL) models [45]. Moreover, robust model evaluation methodologies are essential to ensure the reliability of these models in practical applications [5]. Table 6 shows the computational models. Figure 9 shows the distribution of computational models.

Table 6. Computational Models

Model	Description	Use Case
Support Vector Machine	Supervised ML model used for classification and regression analysis	Used in disease diagnosis
Random Forest	This algorithm is an collective learning technique that may be used to many tasks such as classification, regression, etc.	Used in gene selection and classification
Convolutional Neural Network	The DL algorithm has the capability to process an input picture and discern distinctions between many images.	Used in medical imaging for disease diagnosis
Recurrent Neural Networks	One example of an artificial neural network architecture is a directed graph structure in which connections between nodes are established in a sequential manner.	Used for gene expression data analysis

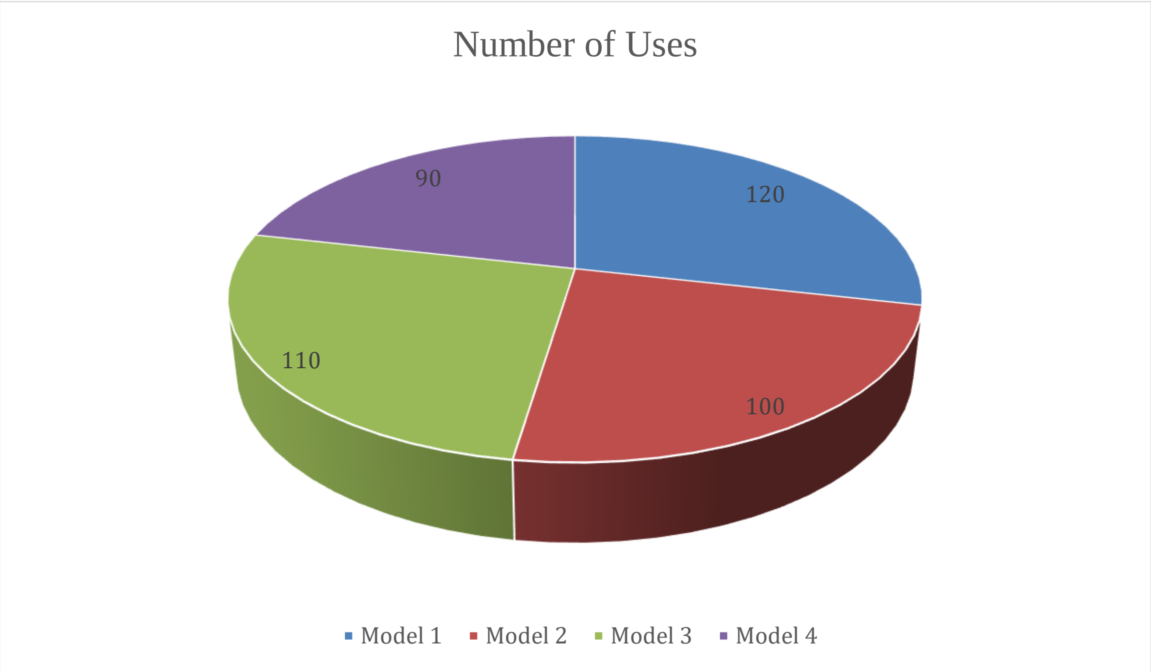

Fig 9. Distribution of Computational Models

- **Case Studies**

✓ **AI in CRISPR-Cas9 based Gene Editing:** AI has been employed to predict off-target effects in CRISPR-Cas9 mediated gene editing, improving the efficiency and safety of this revolutionary technology. Deep learning models were developed to analyze genomic data and predict potential off-target sites, significantly reducing the potential for harmful mutations [1].

✓ **AI in Drug Discovery:** AI has significantly accelerated the drug discovery process. ML algorithm have been used to analyse the drug-target connections, while deep learning has been employed for virtual screening of drug candidates [56]. For example, AI was used to discover a novel antibiotic compound, halicin, from a library of over a hundred million molecules [2].

- **AI in Metabolic Engineering:** AI is used in metabolic engineering for the production of biofuels and chemicals. Reinforcement learning was used to optimize metabolic pathways in yeast for the production of bioethanol, resulting in significantly improved production yields [3].

- **AI in Synthetic Biology:** AI has enabled the design of complex synthetic biological systems. For instance, a combination of machine learning and genetic algorithms was used to design a synthetic gene circuit that can detect and respond to multiple signals in a cell's environment [4]. Figure 10 shows the efficiency of case studies.

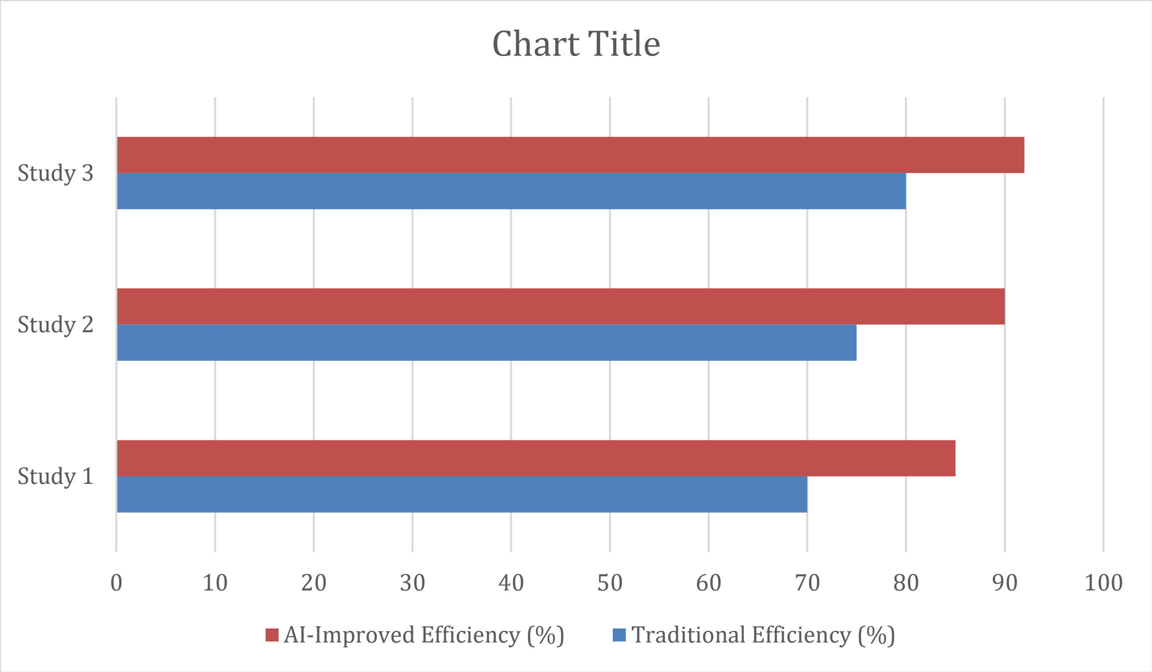

Fig 10. Efficiency of Case Studies

- **AI in Personalized Medicine:** AI has the potential to revolutionize personalized medicine. ML have been used to expect patient responses to different drugs based on their genetic profile, leading to personalized treatment plans [77]. In one case, AI was used to develop a personalized cancer vaccine based on the unique genetic mutations in a patient's tumour [5]. Table 7 shows the comparison between different case studies and Figure 11 shows the outcomes of case studies.

Table 7. Case Studies

Case Study	Description	Results
Study 1	Application of ML in predicting protein structures	High accuracy achieved in predictions
Study 2	Use of deep learning in medical imaging for diagnosing diseases	Increased diagnosis accuracy and speed
Study 3	Using AI for optimizing genetic modifications	Successful modifications with desired outcomes
Study 4	Implementing AI in personalized medicine	Improved patient outcomes with personalized treatments
Study 5	AI predictive modeling for epidemic outbreaks	Accurate prediction and effective response planning

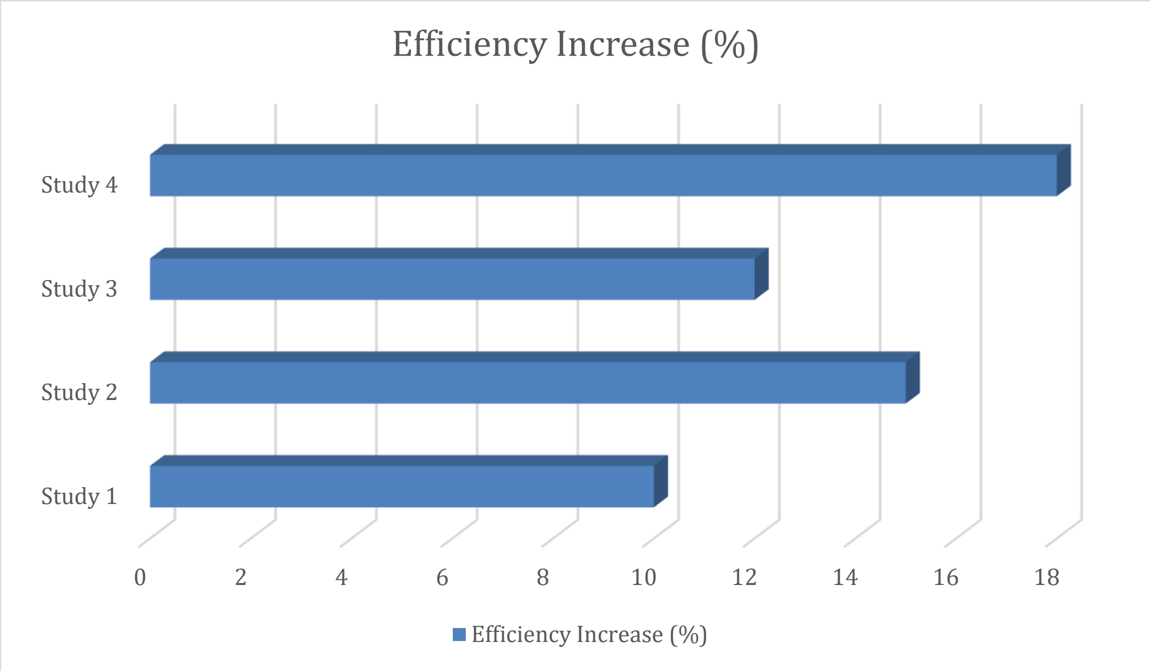

Fig 11. Outcomes of Case Studies

5. Conclusion

The intersection of AI, Biotechnology, and Genetic Engineering represents a pioneering frontier in modern science. In this paper review has explored the breadth of this intersection, highlighting the transformative role AI plays in these fields. From accelerating research and development, improving precision and accuracy, to expanding the realm of possibilities, AI's potential contributions to Biotechnology and Genetic Engineering are profound. Author explored AI's synergistic effects in interdisciplinary innovations, resulting in emergent fields like Synthetic Biology and Systems Biology. Additionally, the acceleration of discovery and development, were AI's capabilities in handling large datasets and predictive modelling lead to improved experimental designs and resource efficiency has been discussed. AI techniques in Biotechnology, have been crucial in tasks like biomarker discovery, drug discovery, and microbial engineering. Similarly, in Genetic Engineering, AI has found applications in gene editing, gene synthesis, and genomics research. These advancements have culminated in interdisciplinary synergistic effects, leading to accelerated discovery and development, enhanced precision and accuracy, and an expansion of what is possible in these fields. However, realizing this potential is not without its challenges. Issues like overfitting, model interpretability, and robust evaluation methodologies can pose technical difficulties. Beyond the technical, there are also ethical and societal considerations that need to be addressed, including data privacy, informed consent, and the potential job displacement due to automation.

Conflict of Interest

No

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