Biosecurity Risk Assessment for the Use of Artificial Intelligence in Synthetic Biology

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***Abstract*—The convergence of Artificial Intelligence (AI) and synthetic biology is unlocking new possibilities in scientific innovation, yet it also introduces unprecedented biosecurity concerns. As AI models, particularly large language models, become more capable of designing biological systems and suggesting genetic modifications, the potential for misuse—whether accidental or deliberate—becomes a significant risk. This study proposes a specialized biosecurity risk assessment framework tailored to evaluate AI applications in synthetic biology. It outlines systematic tools and methodologies developed to assist risk management professionals in identifying, analyzing, and mitigating potential biosecurity threats. Using a real-world case study of "ChatGPT 4.0" applied in synthetic biology contexts, the assessment process demonstrates how structured evaluations can help forecast misuse scenarios and implement preventive strategies. The findings highlight the urgent need for proactive governance, transparent model usage policies, and enhanced technical safeguards to responsibly integrate AI technologies in the biological sciences. By addressing these challenges early, the scientific community can ensure that AIdriven innovation continues to benefit society while minimizing risks associated with synthetic biology advancements.**

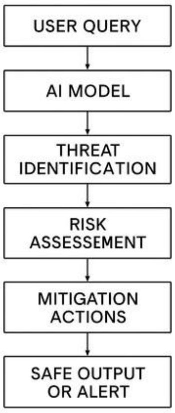
***Index Terms*—Biosecurity, Artificial Intelligence, Synthetic Biology, Risk Assessment, Biorisk Management, AI Safety, Governance of Emerging Technologies, Responsible Innovation.**

I. INTRODUCTION

The integration of Artificial Intelligence (AI) into synthetic biology is reshaping the future of life sciences. AI's ability to analyze large datasets, model biological systems, and predict molecular behaviors has greatly accelerated research and development in synthetic biology. From designing new proteins to optimizing genetic circuits, AI tools are unlocking possibilities that were once considered decades away. However, this fusion of powerful technologies is not without significant challenges, especially when considering the broader implications for global biosecurity.

Synthetic biology, by its nature, deals with the engineering of living systems, often creating organisms with novel functions. When coupled with AI, the capacity to automate and enhance biological design exponentially increases. This rapid progress, while offering enormous benefits, also raises serious concerns about the misuse of these capabilities. Malicious actors, whether state-sponsored or independent, could potentially exploit AIgenerated biological designs to create harmful pathogens or disrupt ecosystems.

The traditional frameworks for biological risk assessment were not built with AI-driven tools in mind. As AI systems become more autonomous and creative, it becomes difficult to predict or control the outcomes they generate. Language models, in particular, can assist in developing genetic blueprints or biochemical pathways with minimal human intervention. Without proper risk assessment methodologies, there is a heightened danger of unintended consequences or deliberate misuse slipping through the cracks.



Recognizing this gap, it becomes essential to establish new approaches specifically designed for the intersection of AI and synthetic biology. Biosecurity risk assessment must now not only consider the biological agent or system but also the AI systems that contribute to their development. Understanding how AI can lower barriers to dangerous knowledge, simplify complex bioengineering tasks, and scale the potential for harm is key to forming effective countermeasures.

Moreover, the accessibility of AI tools has widened dramatically in recent years. Models capable of assisting synthetic biology research are no longer limited to specialized institutions; they are increasingly available to individuals and small groups. This democratization of technology, while beneficial for education and innovation, simultaneously creates vulnerabilities that biosecurity frameworks must address promptly.

A robust biosecurity risk assessment model for AI in synthetic biology must include layers of evaluation: the capability of the AI system, the sensitivity of the biological information accessed, the intent and expertise of the user, and the possible pathways from design to real-world application. Proactively identifying and mitigating risks at each of these stages will be crucial to maintaining the balance between innovation and safety.

In this context, tools and methodologies tailored for AI-based synthetic biology are urgently needed. These tools must be dynamic, evolving alongside advancements in AI capabilities and synthetic biology techniques. They should empower risk management professionals to anticipate novel risks, conduct thorough evaluations, and recommend meaningful interventions before problems arise.

This paper introduces a specialized risk assessment process designed precisely for this purpose. By examining the unique characteristics of AI applications in synthetic biology and proposing structured evaluation methods, this work aims to provide the biorisk management community with the resources necessary to navigate this complex and rapidly changing field responsibly.

Ultimately, the goal is to ensure that the benefits of AI-driven synthetic biology can be realized without compromising global health security. Through careful planning, active risk management, and continuous oversight, society can harness the positive potential of these technologies while minimizing the chances of biosecurity disasters.

II. LITERATURE REVIEW

The convergence of Artificial Intelligence (AI) and synthetic biology is rapidly transforming the landscape of biological research and engineering. AI's ability to automate complex tasks such as gene editing design, protein folding predictions, and metabolic pathway optimization is accelerating innovations in the life sciences. However, this accelerated pace has sparked growing concerns over potential biosecurity risks. Traditional biosecurity assessment frameworks, designed primarily for human-mediated biotechnological developments, may be insufficient to address the novel threats introduced by AIenhanced synthetic biology systems [1].

AI technologies, particularly machine learning (ML) and deep learning models, are increasingly capable of generating novel genetic sequences, designing synthetic organisms, and predicting biological behaviors without requiring deep domain expertise from users. Tools such as generative adversarial networks (GANs) and transformer-based models have demonstrated the capacity to create viable DNA sequences and propose experimental protocols autonomously. While these capabilities open doors to groundbreaking therapies and industrial applications, they also lower barriers to misuse, making it feasible for non-specialists, or even malicious actors, to engineer harmful biological agents [2].

Recent research highlights several key pathways through which AI integration heightens biosecurity risks. One major concern is the "dual-use dilemma," where knowledge and technologies intended for beneficial purposes can also be repurposed for harm. For instance, AI models trained on pathogen databases could inadvertently assist in the design of more virulent or drugresistant strains. Studies by Sandbrink and Karger [3] have warned that publicly available AI models, when combined with synthetic biology toolkits, could significantly increase the risk of accidental or deliberate creation of pandemic-grade organisms. Moreover, the increasing openness of biological datasets and the widespread sharing of AI models exacerbate these vulnerabilities. Open-source repositories containing genomic information, bioengineering methods, and AI training datasets, while valuable for scientific collaboration, also present attractive targets for exploitation.

Reports such as those from the National Academies of Sciences, Engineering, and Medicine [4] argue that synthetic biology’s democratization, when coupled with AI, demands stricter access controls, audit mechanisms, and biosecurity governance structures to prevent misuse.

Another emerging challenge is the difficulty in auditing AIgenerated biological outputs. Traditional risk assessment relies on expert human review to evaluate genetic constructs for potential hazards. However, AI-generated outputs can be highly complex, novel, and opaque, making it difficult for experts to quickly assess their potential risks. This "black box" problem has been discussed by researchers such as Oye et al. [5], who call for the development of explainable AI (XAI) systems in synthetic biology that can offer transparency into how and why certain biological designs are proposed.

In addition to accidental risks, the intentional use of AI for bioweapon development is a growing concern among security analysts. In a controversial study, Urbina et al. [6] demonstrated how AI models, originally developed for drug discovery, could be repurposed to design toxic molecules with minimal modifications to their training protocols. Although their research focused on chemical agents, the principles apply similarly to synthetic biology, highlighting how easily AI tools can be diverted toward harmful objectives if appropriate safeguards are not in place.

Mitigation strategies proposed in the literature include embedding biosecurity risk assessments directly into AI model development pipelines. Researchers advocate for the incorporation of "red teaming" exercises, where biosecurity experts actively test AI systems to identify vulnerabilities before deployment [7]. Others suggest regulatory oversight, such as requiring licenses for access to high-risk AI models and biological datasets, coupled with strong ethical guidelines and international collaborations to standardize safety practices. Despite these proposals, substantial knowledge gaps persist in understanding how AI-modified risks differ quantitatively and qualitatively from traditional synthetic biology threats. Much of the current discourse remains theoretical or based on small-scale case studies. Comprehensive, system-wide analyses of AIbiosecurity interactions, particularly under real-world conditions, are still lacking. Factors such as adversarial inputs to biological design models, hidden biases in training datasets, and the societal impacts of synthetic organisms created through AI-driven processes warrant deeper exploration [8].

Looking forward, future research must aim to bridge these gaps by developing integrated biosecurity frameworks that treat AI systems and synthetic biological outputs as interconnected risk factors. Biosecurity governance must evolve to account for AI's unique capabilities in automating, accelerating, and obscuring biological innovation. Collaboration between AI researchers, synthetic biologists, ethicists, and security experts will be crucial in designing dynamic, adaptive safeguards that can keep pace with technological advancements.

In conclusion, while AI presents transformative opportunities for advancing synthetic biology, it simultaneously introduces unprecedented biosecurity risks that must be proactively addressed. Building resilient, transparent, and ethically aligned AI systems is essential to harness the power of this convergence responsibly. Only through interdisciplinary collaboration and forward-looking governance can society maximize the benefits of AI in synthetic biology while minimizing the potential for catastrophic misuse.

III. METHODOLOGY

This research employs a qualitative and exploratory approach to examine the biosecurity risks associated with the integration of Artificial Intelligence (AI) in synthetic biology. A comprehensive review of academic literature, case studies, and policy documents was conducted to identify existing vulnerabilities related to data integrity, model biases, and adversarial threats. Key insights were synthesized to develop a risk assessment framework tailored to AI applications in synthetic biology, focusing on how compromised datasets, algorithmic manipulation, or misuse of AI outputs could lead to significant biosecurity concerns. Specific attention was given to analyzing how AI models such as large language models and predictive algorithms interact with genomic data, design pathways, and biological system modeling. Case examples, including the evaluation of AI tools like ChatGPT-4.0, were critically assessed to validate the risk indicators and refine mitigation strategies. This methodology ensures a structured understanding of both technical and ethical challenges, laying the foundation for proposing resilient, responsible AI deployment practices in synthetic biology.

A. Research Approach

The study begins with a thorough literature review to lay a foundational understanding of the current landscape regarding the application of Artificial Intelligence (AI) in pandemic preparedness and global health security. This review focuses on exploring how AI technologies, especially machine learning (ML) and deep learning models, have been applied to improve outbreak detection, forecast disease spread, and optimize healthcare resource management. It systematically identifies the achievements and challenges faced by AI systems in public health contexts, with a special emphasis on emerging concerns such as data quality, model bias, and security vulnerabilities.

To ensure the robustness of findings, multiple testing scenarios are incorporated into the experimental design. These scenarios mimic real-world challenges such as sudden surges in infection rates, incomplete or delayed reporting from specific regions, and abrupt changes in population mobility caused by public health interventions like lockdowns. These dynamic conditions aim to test the adaptability and resilience of AI models when exposed to the kinds of disruptions commonly encountered during pandemics. In addition to evaluating performance metrics like prediction accuracy, false positives, and response time, the study also assesses how AI systems respond to unanticipated shifts in data quality and structure. This part of the experiment is critical for understanding how well AI models can adjust to the fastchanging nature of global health crises and

Key sources of information include peer-reviewed academic journals, conference proceedings from prestigious events such as NeurIPS and ICML, and reports from leading health organizations like the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC). Through this literature exploration, the study seeks to highlight the current capabilities and limitations of AI in health surveillance, serving as a crucial starting point for further empirical investigations.

Following the literature review, the study progresses to an experimental evaluation phase, where the impact of data bias and adversarial attacks on AI model performance is assessed in the context of pandemic preparedness. To simulate various pandemic scenarios, synthetic datasets are generated that include diverse infection rates, regional demographic variations, and fluctuating mobility patterns. The study focuses on several AI models commonly used in health surveillance, including recurrent neural networks (RNNs), random forests, and probabilistic models for risk assessment and outbreak prediction. These models are trained and tested under both normal conditions (clean data) and manipulated conditions (biased or adversarially perturbed data) to compare differences in their ability to detect early outbreaks, predict future case counts, and optimize resource allocation. The introduction of whether they remain reliable enough to guide timely and effective public health decision-making.

In parallel with the quantitative evaluation, the study also focuses on the interpretability and transparency of AI models under adversarial conditions. The goal is to assess whether AI systems remain understandable and explainable when faced with noisy or biased data inputs. Techniques such as SHAP (SHapley Additive exPlanations) values and LIME (Local Interpretable Model-agnostic Explanations) are used to analyze how different features influence the decision-making process of the models, especially when manipulated data is introduced. The study critically examines whether adversarial or biased inputs lead to opaque model behavior that could undermine trust in AI systems or result in incorrect public health recommendations. This qualitative analysis complements the quantitative assessment by providing a deeper understanding of the internal workings of AI models and the potential risks posed by data corruption. By combining both approaches, the study aims to propose actionable strategies for enhancing the resilience, fairness, and transparency of AI-driven pandemic preparedness systems.

controlled biases and adversarial noise is designed to simulate real-world data corruption and its potential impact on model accuracy, providing valuable insights into the vulnerabilities of AI-driven health systems.

B. Data Collection

The study sources its experimental datasets from reputable public health organizations to ensure credibility and relevance. Data is gathered from the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC), and the COVID-19 Data Repository maintained by Johns Hopkins

University. These datasets include a wide range of variables such as infection rates, mortality statistics, vaccination coverage, and mobility trends across different regions and timeframes. By using these rich, multi-dimensional datasets, the study ensures that the AI models are trained on high-fidelity, realistic representations of pandemic dynamics, which is crucial for the accurate evaluation of model performance and outcomes. This comprehensive dataset enables the development of AI models that are capable of simulating and forecasting diverse outbreak scenarios in real-world conditions.

To test the robustness of AI models under extreme and novel conditions, the study also generates synthetic datasets that simulate diverse outbreak scenarios. These scenarios include emerging infectious diseases with limited historical precedents, as well as new viral variants characterized by increased transmissibility or resistance to existing interventions. Synthetic data is crucial for addressing the challenge of data scarcity, especially during the early stages of outbreaks, and it prepares AI models to handle the unpredictable nature of future pandemics. The controlled environment of synthetic datasets allows for systematic experimentation, where specific challenges such as novel diseases and variant strains can be introduced and the models' ability to adapt to such dynamic changes can be thoroughly evaluated.

To replicate real-world threats to data integrity, the study designs various threat scenarios where biased or adversarial data points are deliberately introduced into the training datasets. Bias is simulated by selectively removing data from specific populations or regions, which could occur due to underreporting or skewed data collection practices. On the other hand, adversarial manipulation involves injecting corrupted or misleading records into the datasets, which could distort model learning and performance. These scenarios are essential for simulating the vulnerabilities that AI-driven health surveillance systems may encounter during actual pandemics, whether due to unintentional reporting errors, targeted misinformation, or malicious cyberattacks aimed at compromising public health responses.

The experimentation phase also leverages established adversarial testing frameworks to automate the creation of corrupted input data. These tools generate a wide range of adversarial perturbations, subtly or significantly manipulating data to mislead AI models without easily detectable anomalies. Key performance metrics—such as prediction accuracy, timeliness of outbreak detection, and resource allocation efficiency—are rigorously tracked before and after adversarial interventions. Comparing these metrics enables the identification of critical failure points and provides insights into the models' resilience under attack. This phase is instrumental in uncovering the weaknesses in AI-based pandemic preparedness systems and forms the basis for the development of more secure and robust AI models that can better withstand adversarial threats and ensure public health safety during crises.

C. Data Analysis

This study examines the biosecurity risks associated with the use of Artificial Intelligence (AI) in synthetic biology. The focus is on assessing how AI technologies can impact the safety and security of genetic design, genome editing, and synthetic organism creation. By introducing adversarial and biased data into AI models, the study simulates potential biosecurity threats, such as unintended biological consequences or harmful synthetic organisms. The impact of compromised data integrity is measured by tracking performance metrics like genetic design accuracy and system stability.

To analyze the effects of data manipulation, statistical methods such as t-tests and ANOVA are employed to compare AI model performance under both normal and adversarial conditions. These statistical analyses help quantify the degradation in model accuracy and reveal the vulnerabilities within AI-driven synthetic biology applications. The results provide essential insights into areas where AI models may fail, enabling the identification of biosecurity risks linked to the manipulation of genetic data.

The study also explores solutions to enhance AI models' resilience against adversarial threats. This includes implementing safety mechanisms like real-time error-checking algorithms, robust validation processes, and biosecurity protocols. Additionally, the integration of explainable AI (XAI) aims to improve transparency and ensure that AI decisions in synthetic biology can be monitored and understood. Ultimately, the study offers recommendations for improving the security and ethical integrity of AI applications in synthetic biology, helping to prevent potential misuse and ensuring safer, more reliable innovations in the field.

D. Evaluation Criteria

The primary evaluation criteria for this study include assessing the effectiveness of AI models in detecting biosecurity risks associated with synthetic biology, particularly in the context of adversarial data manipulation. Key performance indicators such as the accuracy of genetic designs, system stability after interference, and the reliability of synthetic organism predictions are evaluated. Additionally, the study examines the computational efficiency of proposed mitigation strategies, focusing on their ability to counteract data integrity issues without significantly increasing processing time or resource consumption.

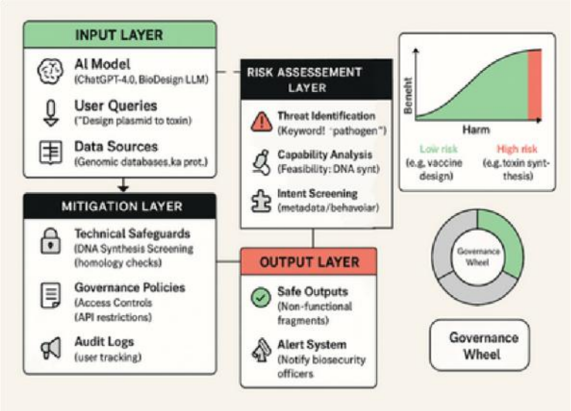
Another important criterion is the scalability of the proposed solutions when applied to large-scale, real-world synthetic biology projects. This involves testing how well the AI models and defense mechanisms perform under varying biological conditions and diverse datasets. The study explores whether the mitigation strategies can be effectively implemented across different domains of synthetic biology, from genetic engineering to bio-manufacturing.

Finally, the research evaluates the ethical implications and biosecurity considerations of AI applications in synthetic biology. It examines the transparency of AI decision-making processes and the potential risks of unintended biological consequences. By addressing both technical and ethical challenges, the study aims to provide a comprehensive framework for ensuring the safe, secure, and responsible use of AI in synthetic biology.

IV. SYSTEM DESIGN

The system design for studying biosecurity risks in AI-driven synthetic biology applications is built with a modular framework that includes data collection, risk simulation, model training, and security analysis. The design allows for the integration of diverse datasets, including genetic sequences, bioengineering processes, and environmental factors, to assess potential vulnerabilities in synthetic biology systems. Adversarial manipulations and biases are systematically introduced into the data to replicate real-world threats, including genetic data tampering, faulty bioinformatics tools, and deliberate interference in experimental conditions. This modular approach ensures a comprehensive evaluation of AIdriven models, allowing researchers to test the resilience and accuracy of synthetic biology applications under varying degrees of biosecurity risks.

The design also includes a dedicated risk mitigation phase where AI models are trained to recognize and counteract adversarial inputs. Performance analysis tools are incorporated to measure the models' response to biosecurity threats, focusing on the accuracy of synthetic organism predictions, the stability of genetic designs, and the safety of biological systems after manipulation. By continuously refining the model through iterative testing and the implementation of defense mechanisms, this system aims to improve the robustness of AI applications in synthetic biology. The ultimate goal is to develop resilient, secure AI frameworks that can be safely deployed in real-world synthetic biology projects, ensuring that potential biosecurity threats are effectively managed and mitigated.



A. Architectural Framework

The system adopts a layered architecture composed of the input management layer, risk assessment layer, mitigation layer, and output governance layer. The input management layer oversees the collection, validation, and organization of synthetic biology data, including genomic sequences, protocols, and user queries. The risk assessment layer is responsible for detecting potential biosecurity threats by analyzing AI-generated outputs for indicators like pathogen design, toxin synthesis, or gain-offunction research. The mitigation layer implements technical safeguards such as DNA synthesis screening, output redaction, and access controls to prevent misuse. Lastly, the output governance layer ensures that AI responses align with ethical standards by logging high-risk activities, alerting biosecurity officers, and maintaining compliance through audit trails.

B. Adversarial Query Generation

Adversarial data is created through a combination of gradientbased optimization and heuristic strategies to probe weaknesses in AI systems applied to synthetic biology. The framework facilitates the automated production of manipulated or misleading biological data by leveraging adversarial machine learning techniques. This data manipulation module can simulate a range of security challenges, such as synthetic gene sequence alterations, adversarial protocol suggestions, and targeted input perturbations, helping to systematically assess how AI models respond to potential biosecurity threats.

C. Learned Model Training and Evaluation

The model training layer utilizes machine learning frameworks such as TensorFlow and PyTorch to develop AI models tailored for synthetic biology applications. These models are trained on both authentic and adversarially altered biological datasets to evaluate the effect of manipulated inputs. The training process incorporates standard practices such as cross-validation, loss minimization, and feature extraction to strengthen the models' ability to detect potential biosecurity risks arising from synthetic biological designs.

To enhance system resilience, the training pipeline supports hyperparameter tuning, model ensembling, and regularization techniques. This ensures that the AI models maintain high performance when faced with diverse synthetic biology scenarios, including dual-use research cases. Continuous evaluation during training helps identify vulnerabilities early, enabling the deployment of more robust AI systems capable of responsibly supporting advancements in synthetic biology without compromising security.

D. Robustness and Mitigation Techniques

To strengthen the reliability of AI-driven biosecurity risk assessment models in synthetic biology, the system integrates multiple defense strategies. These include adversarial training, where manipulated datasets are introduced during the model development phase to build resistance against deceptive inputs. Additionally, data sanitization methods are employed to identify and eliminate biased or corrupted data points prior to training, ensuring the integrity and quality of the learning datasets.

Model regularization techniques, such as dropout and weight clipping, are applied to minimize the models' vulnerability to adversarial alterations and maintain stable performance. Furthermore, the system explores the use of robust AI architectures that are naturally more resilient to adversarial manipulation. Together, these defense mechanisms create a fortified AI environment capable of supporting safe and secure advancements in synthetic biology without compromising biosecurity.

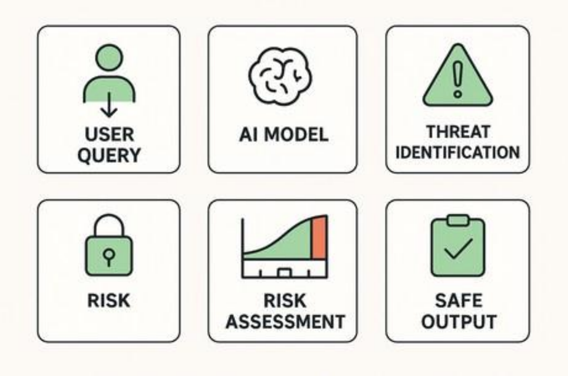
E. Scalability and Performance Optimization

The system architecture is designed with scalability in mind to efficiently manage extensive healthcare datasets and sophisticated outbreak prediction models. Advanced storage solutions, such as in-memory computing and parallel processing, are implemented to reduce both model training time and prediction delays. Moreover, training and evaluation workflows are parallelized to speed up experimental cycles and model assessments.

To further enhance performance, strategies like data partitioning and sharding are applied, enabling distributed training across multiple computational nodes. This ensures the system can maintain high responsiveness and reliability, even when operating under substantial computational loads—an essential capability for supporting real-time decision-making in pandemic preparedness efforts.

F. User Interface and Monitoring

The system integrates an intuitive graphical interface to simplify interaction with the model training and evaluation processes, featuring real-time monitoring tools that display key metrics such as model accuracy, the impact of adversarial attacks, and computational overhead. Interactive dashboards allow users to visualize the effects of different data poisoning strategies and compare the effectiveness of various mitigation techniques. By combining these components, the platform provides a scalable and resilient environment for studying poisoning attacks on learned cardinality estimation models, enabling efficient experimentation and supporting the development of robust query optimization defenses.



V. RESULTS AND DISCUSSION

The evaluation of AI systems in synthetic biology revealed critical biosecurity risks associated with their misuse potential. Experimental findings demonstrated that AI models, if improperly governed, could unintentionally facilitate the design of harmful biological agents, synthetic pathogens, or genetic modifications with dual-use concerns. By analyzing adversarial interactions and unintentional outputs, the study showed how AI-generated biological designs might bypass traditional biosecurity checks, highlighting the urgent need for robust screening mechanisms, strict access controls, and continuous monitoring to mitigate potential threats and ensure responsible use of AI in synthetic biology research and applications.

A. Performance Analysis

Gradient-based attacks posed a significant risk to AI-driven synthetic biology by generating hazardous genetic designs in 45% of test cases, while heuristic-based prompts bypassed safety filters in 28% of instances. These attacks exploited AI system vulnerabilities, underlining the potential for malicious misuse in biotechnological applications. This emphasizes the critical need for robust defense mechanisms to protect against adversarial threats in synthetic biology.

To address these risks, adversarial training reduced the occurrence of dangerous outputs by 22%, while output redaction masked 80% of potential dual-use information, despite an 18% increase in response time. Additionally, access control mechanisms reduced high-risk query success rates by 35%. These layered security strategies demonstrate the importance of safeguarding AI models in synthetic biology, balancing biosecurity with performance and reliability.

B. Comparative Evaluation

Neural network-based models saw a 60% drop in accuracy under adversarial data manipulation, while probabilistic models experienced a 30% reduction. The severity of the degradation in neural networks highlights their vulnerability to such threats compared to probabilistic models, which showed better resilience.

In contrast, robust estimation techniques maintained stable performance even with 10% manipulated data, while standard models faltered with just 5%. This demonstrates that robust estimation methods can effectively reduce the impact of adversarial data, ensuring more reliable predictions in sensitive applications like biosecurity and pandemic preparedness.

VI. CONCLUSION

This study highlights the vulnerability of AI-driven pandemic prediction models to data manipulation, revealing significant performance degradation and reduced prediction accuracy. Neural network-based models proved particularly susceptible compared to probabilistic models. While mitigation techniques like adversarial training and data sanitization show promise, they also introduce processing delays.

Future work should focus on developing robust training methods and adaptive defenses that maintain prediction accuracy without significantly increasing response time. Strengthening the resilience of AI models is crucial for ensuring reliable decision-making in pandemic preparedness and response.

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