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Artificial Intelligence in HIV Diagnosis and Treatment: A Comprehensive Review

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Review Article

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ABSTRACT

Objective: This review examines the applications of Artificial Intelligence (AI) in HIV diagnosis, treatment optimization, and epidemiological modeling. It explores how AI enhances early detection, personalizes antiretroviral therapy (ART), and supports public health strategies while addressing ethical and accessibility challenges.
Methods: A systematic literature search was conducted in PubMed, Scopus, and Web of Science for peer-reviewed studies published between 2010 and 2024. Relevant policy documents from WHO and UNAIDS were also reviewed. Studies on AI applications in HIV diagnosis, treatment, and epidemiology were included, while non-peer-reviewed, non-English, and unrelated studies were excluded. Selected studies were categorized into key thematic areas.
Results: Machine Learning (ML) techniques, particularly supervised models like support vector machines (SVM) and random forests (RF), have significantly improved HIV diagnosis by enhancing accuracy in early detection. Deep Learning (DL)-assisted drug discovery methods, such as generative adversarial networks (GANs), have accelerated ART regimen development. Epidemiological modeling has benefited from AI's ability to analyze large datasets, informing targeted interventions. However, challenges such as algorithmic biases, data privacy concerns, and limited AI adoption in low-resource settings remain barriers to implementation.
Conclusion: AI has transformed HIV management by improving diagnosis, treatment, and epidemic control. Future research should focus on refining AI models, increasing data inclusivity, and ensuring ethical and equitable AI integration into global healthcare systems to maximize its impact.

Keywords: Artificial Intelligence, HIV Diagnosis and Treatment, Machine Learning, Deep Learning, Neural Networks, Epidemiological Modeling, Antiretroviral Therapy (ART)

HIV Tanı ve Tedavisinde Yapay Zeka: Kapsamlı Bir Derleme

Sistematik Derleme

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ÖZET

Amaç: Bu derleme, Yapay Zekâ'nın (YZ) HIV tanısı, tedavi optimizasyonu ve epidemiyolojik modellemedeki uygulamalarını incelemektedir. YZ'nin erken teşhisi nasıl geliştirdiği, antiretroviral tedaviyi (ART) nasıl kişiselleştirdiği ve halk sağlığı stratejilerini nasıl desteklediği ele alınırken etik ve erişilebilirlik zorlukları da tartışılmaktadır.
Yöntem: 2010-2024 yılları arasında yayımlanan hakemli çalışmaları içeren sistematik bir literatür taraması PubMed, Scopus ve Web of Science veritabanlarında gerçekleştirilmiştir. Ayrıca, Dünya Sağlık Örgütü (WHO) ve UNAIDS'in ilgili politika belgeleri incelenmiştir. HIV tanısı, tedavisi ve epidemiyolojisinde YZ uygulamalarına odaklanan çalışmalar dâhil edilirken, hakemli olmayan, İngilizce dışındaki dillerde yayımlanmış ve konu ile ilgisiz çalışmalar hariç tutulmuştur. Seçilen çalışmalar, temel tematik alanlara göre sınıflandırılmıştır.
Bulgular: Makine Öğrenimi (ML) teknikleri, özellikle destek vektör makineleri (SVM) ve rastgele ormanlar (RF) gibi denetimli modeller, HIV teşhisinde erken tespit doğruluğunu artırarak önemli gelişmeler sağlamıştır. Derin Öğrenme (DL) destekli ilaç keşif yöntemleri, özellikle üretici çekişmeli ağlar (GANs), ART (antiretroviral tedavi) rejimi geliştirme sürecini hızlandırmıştır. Epidemiyolojik modelleme, AI'nin büyük veri setlerini analiz etme yeteneğinden faydalanarak hedefe yönelik müdahaleleri şekillendirmeye yardımcı olmuştur. Ancak, algoritmik önyargılar, veri gizliliği endişeleri ve düşük kaynaklı bölgelerde AI'nin sınırlı benimsenmesi gibi zorluklar, uygulamada engeller oluşturmaya devam etmektedir.
Sonuç: YZ, HIV yönetimini tanı, tedavi ve salgın kontrolü açısından dönüştürmüştür. Gelecekteki araştırmalar, YZ modellerinin iyileştirilmesine, veri kapsayıcılığının artırılmasına ve etik ile eşitlik ilkelerine uygun bir şekilde küresel sağlık sistemlerine entegrasyonunun sağlanmasına odaklanmalıdır.

Anahtar Kelimeler: Yapay Zekâ, HIV Tanısı, HIV Tedavisi, Makine Öğrenimi, Derin Öğrenme, Sinir Ağları, Epidemiyolojik Modelleme, Antiretroviral Tedavi (ART).

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Introduction

HIV remains a significant global public health challenge, with an estimated 38 million people living with HIV worldwide as of 2023. Despite advancements in ART, which has transformed HIV from a fatal disease into a manageable chronic condition, substantial gaps persist in early diagnosis, treatment optimization, and epidemic control, especially in low-resource settings. [1,2]

Artificial Intelligence (AI) has emerged as a transformative force across various fields, including healthcare. AI is a broad field encompassing various computational techniques designed to mimic human intelligence. Within AI, Machine Learning (ML) refers to algorithms that enable systems to learn patterns from data and make predictions or decisions without being explicitly programmed. Deep Learning (DL), a subset of ML, utilizes artificial neural networks with multiple layers to process complex data structures, such as medical images, genomic sequences, and clinical records. [3] By leveraging ML and DL techniques, AI has demonstrated remarkable potential in augmenting disease diagnosis, personalizing treatments, and analyzing complex datasets. In the context of HIV, AI applications are revolutionizing the landscape by improving diagnostic accuracy, facilitating drug discovery, and optimizing patient management strategies. [4-6]

Several reviews have explored AI's role in HIV care, primarily focusing on specific aspects such as HIV testing. For instance, a recent systematic review by Jaiteh al. provides an in-depth analysis of AI-driven approaches in HIV diagnostics. [7] However, this study is limited to diagnostic advancements, whereas our review takes a broader, multidisciplinary perspective, covering not only diagnosis but also treatment optimization, epidemiological modeling, and ethical considerations. Furthermore, we highlight region-specific challenges, particularly in low-resource settings such as Turkey, where AI integration faces unique regulatory and infrastructural barriers. By offering a more comprehensive analysis, this review aims to fill existing gaps in the literature and provide a nuanced discussion on AI's transformative potential in HIV care.

This review explores the current state of AI applications in HIV diagnosis and treatment. The paper addresses key developments in leveraging AI for early HIV detection, personalized medicine, and public health interventions. Furthermore, it discusses challenges such as ethical concerns, data privacy, and the accessibility of AI-driven solutions in diverse healthcare settings. By providing a critical assessment of existing literature, this review seeks to highlight the transformative potential of AI in combating HIV and outline future directions for research and implementation.

Methods

A systematic approach was adopted to identify and analyze relevant literature for this review. Databases such as PubMed, Scopus, and Web of Science were searched for peer-reviewed articles published between 2010 and 2024. The search terms included combinations of "HIV," "artificial intelligence," "machine learning," "deep learning," "diagnosis," "treatment," "epidemiology," and "ethical challenges." Additional resources were also reviewed, including conference proceedings and policy documents from organizations such as WHO and UNAIDS.

Selection Criteria for Reviewed Studies

The selection process for reviewed studies was based on specific inclusion and exclusion criteria to ensure relevance and quality. Studies were included if they:

- Focused on artificial intelligence applications in HIV diagnosis, treatment, or epidemiology.
- Provided quantitative performance metrics for AI models, such as accuracy, sensitivity, or specificity.
- Utilized real-world patient data, including clinical, genomic, or imaging datasets.
- Were published in peer-reviewed journals between 2010 and 2024.
- Studies were excluded if they:
- Primarily discussed AI methodologies without clinical validation in HIV-related contexts.
- Were opinion articles, commentaries, or theoretical reviews without experimental results.
- Had insufficient data on AI model performance or lacked clear evaluation metrics.
- Were non-English publications or non-peer-reviewed source.

The selected studies were categorized into thematic areas, including diagnostic advancements, treatment personalization, data analytics, and ethical considerations. The findings were synthesized to provide a comprehensive overview of current trends, challenges, and prospects in the field.

AI in HIV Diagnosis

AI has shown significant promise in improving the accuracy and efficiency of HIV diagnosis. ML and DL algorithms have been employed to analyze complex datasets, identify patterns, and predict outcomes with remarkable precision.

ML algorithms, such as support vector machines (SVM), random forests, and k-nearest neighbors (k-NN), have been instrumental in classifying HIV statuses based on clinical and laboratory data. DL models, particularly CNNs and recurrent neural networks (RNNs) have further advanced diagnostic capabilities by analyzing imaging data, genomic sequences, and biomarker profiles. [3,8]

A notable example is the application of CNNs for analyzing chest X-rays to detect opportunistic infections in HIV-positive individuals, which aids in the comprehensive diagnosis and monitoring of the disease. [9] RNNs, on the other hand, have been utilized for sequence prediction tasks, such as identifying mutations in HIV-1 protease genes that confer drug resistance. [10]

Additionally, deep learning-based computer vision models have been integrated into lateral flow assays for rapid HIV testing. These AI-enhanced diagnostic tools leverage image recognition algorithms to interpret test results with higher accuracy than manual reading, improving sensitivity and specificity in point-of-care settings. [11] One notable example is AI-enhanced lateral flow assays, which employ deep learning-based image recognition to interpret test results with higher accuracy than manual reading methods

Table 1. Comparison of Conventional and AI-Based HIV Diagnostic Methods

Method	Sensitivity	Specificity	Processing Time	Cost	References
PCR *(Polymerase Chain Reaction)*	98-100%	98-100%	6-12 hours	High	Owens et al.[16]
AI-Based SVM Model	82.4%	85.5%	<1 hour	Low	Wu et al. [17]
AI-Based CNN Model (Imaging)	95.9%	99.0%	<30 minutes	Low	Turbé et al.[18]
ML-Based Prediction Model	86.0%	65.6%	Not Specified	Not Specified	Latt et al.[19]
ELISA *(Enzyme-Linked Immunosorbent Assay)*	99-100%	99.7%	24-48 hours	Moderate	Alexander [20]

Accuracy and Effectiveness of AI Models

AI models in HIV diagnosis and treatment are primarily evaluated based on sensitivity, specificity, and accuracy. [12] Sensitivity measures the ability to correctly identify HIV-positive cases, while specificity ensures that false positives are minimized. [13] Accuracy provides an overall measure of the model's correctness. These metrics help determine the reliability of AI applications in clinical practice and public health interventions. [14]

In some cases, additional metrics such as AUC-ROC (Area Under the Receiver Operating Characteristic Curve) and F1-score are used to further refine model evaluation. [15] AUC-ROC measures the trade-off between sensitivity and specificity, making it useful in optimizing model decision thresholds. The F1-score, which balances precision and sensitivity, is particularly relevant in handling imbalanced datasets common in HIV research. [5]

AI -based models have demonstrated the potential to overcome some of these challenges by enhancing sensitivity, specificity, and speed. Compared to conventional diagnostic methods, AI-driven approaches can process large datasets, detect subtle biomarker patterns, and provide rapid results with high accuracy.

Table 1 provides a comparative overview of conventional HIV diagnostic methods and AI-based approaches, highlighting their sensitivity, specificity, processing time, and cost-effectiveness.

Moreover, AI models have proven effective in detecting HIV in early stages, even when viral loads are low. Such capabilities are particularly beneficial in preventing disease progression and reducing transmission risks. [21,22] The integration of AI with next-generation sequencing (NGS) has also enabled the identification of rare and novel HIV strains, improving diagnostic comprehensiveness. [23]

Data Sources and Sample Distribution in AI-based HIV Diagnosis

The datasets used in AI-driven HIV diagnosis vary in size and structure, depending on the study design and the type of AI model applied. For instance, clinical biomarker datasets, such as CD4+ T-cell counts and viral load levels, have been utilized in supervised ML models, often sourced from large-scale studies like the Multicenter AIDS Cohort Study (MACS) dataset, which includes over 6,000 HIV-positive individuals. [24]

In genomic-based HIV diagnosis, NGS data has been incorporated into AI models for mutation detection. Studies using the Stanford HIV Drug Resistance Database (HIVdb) have analyzed over 100,000 sequences to train deep learning models in predicting drug resistance patterns. [25]

Imaging-based AI approaches, such as those using CNNs for opportunistic infection detection, have employed publicly available chest X-ray datasets from hospitals in the US and Africa, containing more than 50,000 labeled images. [26]

These datasets provide diverse training samples, although class imbalance remains a challenge, as the number of HIV-positive patients with detectable imaging markers is significantly lower than other conditions. Additionally, resources detailing HIV-related pulmonary opportunistic infections and their radiological findings are critical for AI-based diagnosis and have been outlined in studies on HIV and lung diseases. [27]

Early Detection and Biomarker Analysis

Early diagnosis remains critical for effective HIV management, as it enables timely initiation of ART, reducing morbidity, mortality, and transmission risks. Recent advancements highlight the use of ML and DL in interpreting complex datasets to predict disease status. AI-driven tools have significantly improved biomarker analysis for early HIV detection. For instance, a study employing CNNs trained on viral load and CD4+ T-cell count datasets achieved an accuracy of 96%, a sensitivity of 94%, and a specificity of 92% in predicting HIV progression. [28] This performance surpasses traditional SVM-based models, which rely on structured clinical data and achieved an accuracy of 91% with a sensitivity of 89% in similar biomarker classification tasks. [29]

Additionally, Transformer-based architectures, such as Bidirectional Encoder Representations from Transformers (BERT) and its biomedical adaptation BioBERT, have demonstrated superior performance in analyzing large-scale genomic datasets. BioBERT achieved an F1-score of 95.2% in identifying HIV-related genetic markers and a classification accuracy of 97% in predicting host-pathogen interactions, outperforming CNN-based methods in sequence analysis tasks. [30]

Moreover, NGS platforms integrated with machine learning-driven mutation detection algorithms (e.g., VirVarSeq, MinVar, DeepChek-HIV) have been used to detect low-frequency HIV drug-resistant variants. These tools have improved detection sensitivity by 15-20% compared to conventional bioinformatics pipelines, enabling the identification of cryptic viremia in patients with undetectable viral loads. [31]

Viral load measurement is another critical diagnostic aspect. AI models leveraging real-time PCR data and NGS outputs have been developed to identify even low levels of viral RNA, enabling earlier detection than standard clinical assays. This approach not only facilitates timely ART initiation but also contributes to identifying patients with cryptic viremia or those at risk of virological failure. [32,33]

Furthermore, AI has been utilized to analyze host genetic factors, such as HLA alleles and polymorphisms in CCR5 genes, which influence susceptibility to HIV infection and disease progression. These insights pave the way for predictive diagnostics and tailored prevention strategies. [34]

Integration of AI in Point-of-Care Diagnostics

AI-powered innovations in point-of-care (POC) diagnostics are revolutionizing HIV testing by enhancing accessibility, accuracy, and efficiency. Portable AI-enabled devices, such as smartphone-based rapid diagnostic tests (RDTs), utilize deep learning models, particularly CNNs, for real-time image analysis of test strips. These systems have demonstrated an accuracy of 98.5%, a sensitivity of 97.2%, and a specificity of 96.8% in detecting HIV antibodies, surpassing traditional rapid tests. [11]

One prominent example is the development of AI-enhanced lateral flow assays that utilize computer vision algorithms to interpret test results with higher accuracy than manual reading. In a study conducted by researchers at University College London (UCL) and the Africa Health Research Institute (AHRI), a deep learning-based computer vision system achieved a classification accuracy of 98.9% in interpreting lateral flow assay results, compared to 92.1% accuracy in manual visual interpretation. [35] Given that this method represents a distinct AI approach in HIV diagnostics, it has also been incorporated into the AI in HIV Diagnosis section, ensuring alignment across different parts of the paper.

AI in HIV Treatment

The integration of AI into HIV treatment strategies has opened new avenues for personalized medicine and improved therapeutic outcomes.

Personalized Medicine and Drug Discovery

AI has revolutionized drug discovery by identifying novel compounds and optimizing existing treatment regimens. ML models have been employed to predict drug efficacy, side effects, and potential resistance patterns, thereby expediting the development of ART. [15,36,37]

AI-Assisted Virtual Screening and Drug Design

AI-driven virtual screening has emerged as a pivotal methodology in accelerating HIV drug discovery, enabling the efficient identification of potential therapeutic compounds by leveraging advanced computational techniques and large-scale molecular data. AI-assisted drug discovery methods, particularly deep learning models such as generative adversarial networks (GANs), have played a crucial role in optimizing ART regimen development by predicting drug-target interactions and identifying novel inhibitors against HIV-specific proteins. [38] Similarly, Wang et al. utilized PubChem datasets and ML techniques to screen large libraries of compounds for potential activity against reverse transcriptase, identifying candidates with improved binding affinity. [39] Gradient boosting models, enhanced with structural and potency data, have achieved high accuracy in predicting ligand binding affinity, with Shapley value analysis highlighting the importance of van der Waals interactions with key protein residues. [30]

GANs and Reinforcement Learning in Drug Discovery

GANs and reinforcement learning algorithms have facilitated the design of novel compounds tailored to HIV-specific targets. These AI-driven approaches have been successfully used to generate de novo molecular structures and optimize drug candidates based on predicted interactions with HIV proteins. [38]

Meanwhile, AlphaFold, developed by Jumper et al., provided highly accurate structural predictions for HIV proteins, enabling researchers to identify key binding sites for integrase and reverse transcriptase inhibitors. Jumper et al.'s AlphaFold, for example, provided accurate structural predictions for HIV proteins, enabling researchers to identify key binding sites for integrase and reverse transcriptase inhibitors. AlphaFold has demonstrated a root-mean-square deviation (RMSD) of <1.5 Å, indicating near-experimental accuracy in protein structure prediction. [40] However, despite these successes, AlphaFold still has limitations, particularly in predicting intrinsically disordered regions and loops, which are crucial for drug design. [41]

Time and Cost Reduction in AI-Based Drug Discovery

AI has significantly accelerated drug discovery processes while reducing associated costs. The integration of AI and ML approaches has facilitated the processing of biological data, leading to reduced time and expenses in drug development. [42]

AI-driven drug discovery optimizes the identification of potential drug candidates, expediting development timelines and reducing the financial burden of bringing new treatments to market. [43] However, many AI applications in drug discovery remain in their early stages and still require human validation to ensure accuracy and reliability.

Additionally, advanced AI and ML frameworks have improved the prediction of drug efficacy, and toxicity thereby lowering development costs and enhancing drug-target interactions. [44]

These advancements highlight AI's crucial role in modern drug discovery and development, offering more efficient and cost-effective therapeutic innovations.

AI-Enhanced High-Throughput Screening (HTS) in HIV Drug Discovery

AI has also revolutionized high-throughput screening (HTS) methodologies, particularly in the context of HIV drug discovery. By integrating AI with HTS, researchers can efficiently analyze vast datasets to identify potential inhibitors targeting HIV proteins, thereby expanding the arsenal of therapeutic options available for HIV management. [45]

Gawehn et al. highlighted the use of deep learning (DL) models to analyze molecular descriptors and prioritize compounds with activity against the RNase H domain of reverse transcriptase, an area of unmet therapeutic need. [46] This approach has the potential to further increase the diversity of available therapeutic compounds and accelerate the drug discovery pipeline.

These advancements underscore AI's pivotal role in modernizing drug discovery and development, offering promising avenues for more efficient and cost-effective therapeutic innovations.

AI-Supported Clinical Application

Clinical decision support systems (CDSS) powered by AI are transforming HIV care by assisting healthcare providers in tailoring ART regimens to individual patient profiles. These systems integrate data from various sources, including genetic markers, comorbidities, and treatment history, to recommend optimized therapeutic strategies. [44] One such system, EuResist, utilizes a combination of three statistical learning models to predict the probability of treatment success based on HIV-1 genotype and supplementary patient data. The system demonstrated 76% accuracy in predicting virological response over an 8-week period, outperforming human HIV drug resistance experts in clinical decision-making. [45] Similarly, the HIV-TRePS (HIV Treatment Response Prediction System) employs Random Forest models to predict the probability of successful treatment response, even in cases where key baseline clinical data (such as genotype or CD4 count) are missing. This system has been validated across a large dataset of over 250,000 patients, achieving an AUC of 0.89 in independent testing. [46] For example, an AI-based CDSS implemented in a South African clinic demonstrated a 20% improvement in treatment adherence and a reduction in virological failure rates. [47] This was primarily due to the system's ability to dynamically adapt ART regimens based on real-time patient data and drug resistance mutations. [48]

Such systems also enable real-time monitoring of patient progress and adaptive adjustments to therapy, enhancing overall treatment efficacy. [49] AI-driven CDSS facilitates continuous patient monitoring, allowing for the detection of early warning signs of treatment failure and timely interventions. Compared to traditional rule-based CDSS, these ML-powered systems offer superior predictive accuracy and adaptability, making them invaluable tools in resource-limited settings. [47]

Mobile Applications and Remote Monitoring

Mobile health (mHealth) applications equipped with AI features are playing an increasingly prominent role in HIV management. These apps offer functionalities such as medication reminders, symptom tracking, and virtual consultations, thereby improving patient adherence to treatment protocols. [50,51]

AI algorithms embedded in these apps analyze user data to provide personalized recommendations and identify early signs of treatment failure. For instance, a mHealth app developed in Kenya uses AI to predict adherence patterns based on user interactions and sends tailored reminders, significantly boosting adherence rates among young adults. [52]

Remote monitoring tools powered by AI have also facilitated decentralized care delivery. Wearable devices that continuously collect and analyze physiological data enable healthcare providers to remotely track patient health and intervene promptly when necessary. [53]

Optimizing ART Regimens

The optimization of ART regimens has greatly benefited from AI applications, which predict drug-drug interactions, minimize adverse effects, and tailor treatments to individual patient needs. Predictive models analyze patient-specific data to identify the most suitable combinations of antiretroviral drugs, improving treatment outcomes and patient satisfaction. [54] These systems incorporate genetic and clinical data to identify optimal ART regimens, enhancing therapeutic efficacy and minimizing adverse effects. ML models like random forests and support vector machines have demonstrated significant accuracy in predicting patient-specific drug responses by analyzing genetic variants linked to drug metabolism, particularly CYP450 enzymes. Pharmacogenomics-based approaches have been instrumental in tailoring HIV therapies by predicting drug efficacy and potential resistance, ensuring improved patient outcomes. [55]

Traditional simulations rely on predefined mathematical models and static assumptions, whereas AI-driven simulations utilize machine learning algorithms to dynamically predict and adapt HIV progression patterns based on real-world patient data. [30]

Moreover, AI-driven simulations of HIV dynamics have been used to test the efficacy of novel treatment strategies in silico before clinical implementation, accelerating the development of innovative therapies. [56] These simulations integrate viral and immune system dynamics to refine dosing schedules and anticipate resistance evolution, significantly accelerating the development pipeline for new ART strategies. [56,57] Furthermore, these simulations allow researchers to predict the consequences of treatment interruptions or dose changes before clinical trials, providing a cost-effective and ethical approach to optimizing ART strategies. [58] However, the ethical implications of AI-driven ART optimization should not be overlooked. While AI enhances treatment personalization, it raises concerns regarding data privacy, algorithmic bias, and transparency in decision-making. Ensuring equitable access to AI-assisted HIV treatments, maintaining patient confidentiality, and mitigating biases in predictive models are crucial factors in the responsible implementation of AI in HIV care. [13,59] These considerations are further discussed in the "Ethical and Social Challenges" section.

Given the diverse applications of AI in treatment, various models have been developed, each leveraging different data types and evaluation metrics. Table 2 provides a comparative overview of the primary AI models used in HIV diagnosis and treatment, summarizing their applications, input data types, and performance metrics.

Table 2: *AI Models Used in HIV Treatment*

AI Model	Application	Input Data Type	Performance Metrics	References
Vela Diagnostics NGS Platform	HIV-1 genotyping & drug resistance analysis	Plasma RNA samples	Identifies major and minor drug resistance mutations with high sensitivity	Vashisht et al.[33]
NGS-based AI model	HIV drug resistance prediction	Whole-genome sequencing data	Detects drug resistance mutations at <20% abundance; higher sensitivity than Sanger sequencing	Ávila et al.[23]
Convolutional Neural Networks (CNNs)	Predicting drug resistance	HIV-1 genetic sequences	High classification performance; importance of biologically relevant features	Steiner et al.[60]
NGS-based AI model	HIV drug resistance prediction	Whole-genome sequencing data	Detects drug resistance mutations with higher sensitivity than population sequencing; 93.5% success rate in high viral load samples	Fogel et al.[32]
CNNs	Virtual screening for new HIV drugs	2D/3D molecular structures & chemical properties	High precision in identifying potential antiviral compounds	Gawehn et al.[46]
Deep Neural Networks (DNNs)	Drug efficacy prediction	Molecular descriptors & chemical structures	Improved accuracy in predicting antiviral drug activity	Gawehn et al.[46]
Random Forest Model	Predicting patient-specific drug responses	Genetic variants (CYP450 enzymes)	85% accuracy (95% CI: 0.79–0.90) in classifying pharmacogenomic variants	Pandi et al.[61]

These AI models have significantly contributed to the advancement of HIV diagnostic accuracy and treatment optimization. By utilizing diverse data sources, AI enhances predictive capabilities and facilitates personalized care strategies. The integration of these models into clinical workflows can further streamline the diagnostic process and support early intervention efforts.

Data Analytics and Epidemiological Models

AI-driven data analytics have transformed HIV epidemiological studies, enabling better understanding and management of the disease at a population level.

Big Data and AI in HIV Epidemiology

AI tools have facilitated the analysis of large-scale datasets, uncovering patterns in HIV transmission and identifying high-risk populations. Predictive models using AI have also been used to forecast epidemic trends and allocate resources efficiently. [62] For instance, predictive analytics have been utilized to study viral transmission clusters using genetic data, which aids in early outbreak detection and intervention planning. Specifically, a CNN model was developed to analyze pairwise genetic distance matrices derived from HIV-1 sequences, successfully identifying active outbreaks with high accuracy (specificity >98%, sensitivity >92%). [63,64] However, AI is not the only automation approach used in HIV epidemiology. Traditional methods such as rule-based systems and statistical models have also been employed.

Rule-based expert systems, which rely on predefined if-then decision trees, were historically used for HIV risk stratification but lacked adaptability to complex datasets. Similarly, logistic regression and Bayesian networks have been widely used to model HIV transmission patterns and disease progression, but they struggle with nonlinear relationships and unstructured data. [12] In contrast, AI-driven models, such as deep learning and reinforcement learning techniques, outperform these traditional methods by handling high-dimensional data and capturing intricate patterns in transmission Dynamics. [65]

For example, a study comparing logistic regression with machine learning models found that AI-based approaches improved predictive accuracy in identifying high-risk populations by nearly 12%. [13] While traditional models remain useful for structured data analysis, AI provides a more robust and adaptive solution for real-time epidemiological modeling and outbreak prediction (Table 3)

***Table 3**: Comparison of Traditional Automation Methods and AI Models in HIV Research*

Category	Method	Example Use Case	Strengths	Limitations	Reference
Traditional Methods	Rule-Based Systems	Patient risk stratification in infectious diseases	Interpretable, works well with structured data	Poor scalability, cannot handle complex patterns	Wiens et al.[12]
Traditional Methods	Statistical Models (Logistic Regression, Cox Models)	Predicting HIV treatment failure	Transparent, widely used in epidemiology	Limited ability to model complex relationships	Wiens et al.[12]
Traditional Methods	Back-Calculation Models	Estimating past HIV incidence	Useful for reconstructing infection history	Requires accurate case reporting, sensitive to missing data	Sun et al.[66]
AI-Based Models	AI-Based Risk Prediction	Identifying high-risk HIV patients for care	Helps target resources effectively	Can introduce racial bias if trained on biased healthcare cost data	Obermeyer et al.[13]
AI-Based Models	AI for Global Health	Disease diagnosis, outbreak prediction, health policy	Uses ML, NLP, signal processing, expert systems for diagnosis & surveillance	Ethical, regulatory, and scalability challenges	Schwalbe et al.[65]
AI-Based Models	Neural Networks for HIV	Predicting HIV drug resistance	Personalized treatment recommendations	Requires large datasets, risk of overfitting	Kuo et al.[67]
AI-Based Models	AI-Driven ART Optimization	ML-driven ART selection using patient biomarkers	Personalized, improves treatment adherence	Data privacy concerns, model interpretability issues	Kuo et al.[67]

Risk Group Identification and Treatment Strategies

AI systems have been employed to segment populations based on risk factors, enabling targeted interventions. These models analyze demographic, behavioral, and clinical data to design effective treatment strategies and prevention campaigns. [68] One study applied ML models to clinical and demographic datasets, identifying individuals with heightened risks of acquiring HIV and sexually transmitted infections within 12 months. [63] Such risk-prediction tools are now being integrated into digital health platforms to encourage targeted testing and preventive measures. [64]

Ethical and Social Challenges

The adoption of AI in HIV diagnosis and treatment raises several ethical and social considerations that must be addressed to ensure equitable and responsible use.

Data Privacy and Security

The use of AI in healthcare requires access to sensitive patient data, raising concerns about data privacy and security. Robust data encryption and governance frameworks are essential to protect patient confidentiality. [59]

Equity and Fairness in AI Implementation

AI applications must be accessible to all, including marginalized populations disproportionately affected by HIV. Efforts must be made to mitigate biases in AI algorithms and ensure equitable access to AI-driven healthcare solutions. [31]

Ethical Considerations in AI-Driven HIV Care

While AI has the potential to transform HIV diagnosis, treatment, and epidemiological modeling, its implementation raises significant ethical concerns. The use of AI in healthcare involves complex issues related to data privacy, patient consent, bias in AI algorithms, and regulatory frameworks. Addressing these ethical challenges is essential to ensure the responsible and equitable deployment of AI-driven healthcare solutions.

Data Privacy and Patient Consent

AI models rely on vast amounts of patient data, often derived from electronic health records (EHRs), genomic sequencing, and real-time monitoring devices. While these datasets enable AI to improve diagnosis and treatment, they also increase the risk of data breaches and unauthorized access. [59]

A major concern in AI-driven HIV care is the potential misuse of sensitive health information. HIV status is a highly sensitive medical condition, and any breach of confidentiality could lead to stigma, discrimination, and psychological distress for patients. [69] Therefore, robust encryption methods, secure data storage, and transparent data-sharing policies are essential to protect patient privacy.

Additionally, informed consent in AI-based healthcare is a critical ethical issue. Many AI systems operate in black-box models, where the reasoning behind predictions is not easily interpretable. This lack of transparency can make it difficult for patients to provide truly informed consent. Ethical AI implementation requires explainable AI (XAI) approaches, where patients and clinicians can understand how AI reaches conclusions. [6]

Algorithmic Bias and Fairness

AI systems can inherit and amplify biases present in the datasets they are trained on, potentially leading to discriminatory outcomes. [13] In the context of HIV care, biased AI models could result in misdiagnosis or unequal access to treatment for marginalized populations. If AI models for HIV detection and treatment are primarily trained on data from high-income countries, they may perform poorly when applied to populations in low-resource settings, where healthcare access and epidemiological factors differ. [65]

To mitigate algorithmic bias, AI developers should:

- Ensure diverse and representative training datasets that include data from different ethnic, geographic, and socioeconomic backgrounds.
- Conduct fairness audits to detect and correct biases before deploying AI models in clinical practice.
- Develop regulatory guidelines to monitor AI fairness in real-world applications. [70]

Legal and Regulatory Challenges

The legal landscape for AI in healthcare is still evolving, and many countries lack clear policies governing AI-driven medical decisions. In regions with strict data protection laws, such as the European Union's General Data Protection Regulation (GDPR), AI developers must ensure compliance with data security and patient consent regulations. [69]

However, in low-resource settings, the absence of regulatory frameworks creates challenges in ensuring accountability and ethical AI deployment. [59] This legal uncertainty raises several concerns:

- Who is responsible if an AI model provides an incorrect diagnosis or treatment recommendation?
- How should AI-driven clinical decisions be integrated into existing medical liability frameworks?
- What safeguards should be in place to prevent AI from making life-altering medical decisions without human oversight?

To address these issues, governments and international health organizations should develop standardized AI regulations, ensuring that AI applications in HIV care are held to the same ethical and legal standards as traditional medical interventions.

Balancing AI Automation with Human Oversight

While AI enhances diagnostic accuracy and treatment recommendations, it should not replace human clinical judgment. Over-reliance on AI can lead to automation bias, where clinicians blindly trust AI-generated results without questioning their validity. [71]

A study on AI-driven CDSS found that when AI systems made incorrect recommendations, clinicians who were over-reliant on AI were less likely to override the system's suggestions, increasing the risk of medical errors. [70]

To ensure safe AI adoption in HIV care, AI should:

- Complement rather than replace human expertise.
- Include mechanisms for human-AI collaboration, where clinicians can override AI predictions when necessary.
- Be continuously monitored and updated to reflect the latest medical knowledge.

Conclusion

Ethical challenges in AI-driven HIV care must be addressed to ensure equitable, fair, and responsible implementation. Strategies such as enhancing data diversity, strengthening regulatory oversight, improving transparency, and ensuring human oversight are essential for maximizing AI's benefits while minimizing risks. As AI continues to evolve, ongoing dialogue between healthcare professionals, policymakers, AI developers, and patient advocacy groups will be crucial in shaping the future of ethical AI in HIV management.

Limitations and Potential Risks of AI in HIV Care

Despite the transformative potential of AI in HIV diagnosis, treatment, and epidemiological modeling, several challenges must be addressed to ensure its effective and ethical implementation in healthcare settings.

Reliability and Reproducibility of AI Models

A significant limitation of AI models in HIV care is their reliability and reproducibility across different populations and healthcare environments. Many AI models are trained on datasets that may not be representative of diverse patient demographics, leading to inconsistencies in real-world applications. For instance, a study found that ML models trained in high-resource settings had significantly reduced accuracy when applied in low-resource settings, where variations in healthcare infrastructure and genetic differences in HIV strains play a role. [12] Ensuring model generalizability requires diverse, high-quality datasets and rigorous external validation, yet many studies lack real-world validation.

Bias and Health Disparities in AI-Driven HIV Care

AI systems inherit biases present in the data they are trained on, potentially exacerbating existing healthcare inequalities. A study published in *Science* found that a widely used commercial prediction algorithm exhibited significant racial bias by using healthcare costs as a proxy for health status. As a result, Black patients—who historically have less access to healthcare—were systematically assigned lower risk scores despite experiencing more severe illnesses. The study estimated that correcting this bias could increase the percentage of Black patients receiving additional healthcare support from 17.7% to 46.5%, demonstrating how algorithmic biases can reinforce existing racial disparities. [13]

In the realm of HIV care, such biases can lead to inaccurate diagnoses or suboptimal treatment recommendations for marginalized populations. AI models predominantly trained on data from North American and European patients may not perform effectively in regions like sub-Saharan Africa and Southeast Asia, where different HIV subtypes and healthcare contexts prevail. This misalignment underscores the necessity of incorporating diverse populations into AI training datasets. Additionally, conducting thorough fairness assessments prior to deploying these models is crucial to mitigate potential biases and ensure equitable healthcare outcomes. [72]

Ethical and Regulatory Challenges in AI Implementation

The adoption of AI in HIV care raises significant ethical concerns, including data privacy, patient consent, and accountability. AI models often rely on vast amounts of patient data from electronic health records (EHRs) and genomic sequencing, which increases the risk of data breaches and unauthorized Access. [59]

Furthermore, legal and regulatory frameworks for AI-driven healthcare applications vary widely across countries, making standardized implementation difficult. For example, the European Union's General Data Protection Regulation (GDPR) has strict data privacy requirements, while the United States lacks a unified AI regulatory policy. [69] This lack of uniformity complicates the deployment of AI-based HIV interventions globally.

Challenges in Real-World Integration and Scalability

Many AI models require advanced computational resources, stable internet connectivity, and trained personnel for implementation—factors that are often lacking in low-resource settings. [73] Additionally, many AI-driven diagnostic tools do not seamlessly integrate with existing hospital information systems, creating barriers to widespread adoption. [6]

A recent study on AI-assisted HIV diagnostics in Africa found that poor interoperability between AI systems and local laboratory software limited clinical adoption, despite the technology's high diagnostic accuracy. [65] Without proper integration strategies, AI tools risk remaining experimental rather than becoming clinically impactful solutions.

Over-Reliance on AI and the Risk of Automation Bias

While AI has shown remarkable accuracy in HIV diagnosis and treatment optimization, there is a growing concern about over-reliance on AI-generated predictions, potentially reducing human oversight and clinical judgment. [70]

Automation bias—the tendency for humans to over-trust automated decisions, even in cases of AI error—has been documented in multiple healthcare settings. A study found that clinicians were less likely to question incorrect AI-generated diagnoses when working under high workload conditions, increasing the risk of medical errors. [71]

To prevent excessive dependence on AI models, healthcare providers should use AI as an assistive tool rather than a replacement for human expertise. Clinicians must critically evaluate AI-generated outputs rather than passively accepting them as infallible.

AI Implementation Challenges in Turkey

While AI adoption in healthcare has gained momentum globally, its integration into the Turkish healthcare system presents unique challenges. Despite Turkey's highly developed public healthcare infrastructure, AI implementation remains limited due to regulatory uncertainty, data-sharing restrictions, and interoperability issues between AI-driven solutions and existing hospital information systems.

One of the primary barriers is the absence of a comprehensive legal framework governing AI applications in medicine. Currently, Turkey lacks dedicated legislation addressing AI in healthcare, and existing regulations primarily focus on general data protection laws, such as the Personal Data Protection Law (KVKK), which is similar to the European General Data Protection Regulation (GDPR). While these regulations ensure data privacy, they also create bureaucratic obstacles for AI-driven research and clinical deployment, as hospitals and research institutions face strict limitations on patient data usage for AI model training. [74]

Additionally, Turkey's AI infrastructure in healthcare is still in its early stages, with limited AI integration into electronic health record (EHR) systems. Unlike in countries where AI is embedded into routine clinical workflows, Turkish hospitals and laboratories still primarily rely on conventional diagnostic and treatment decision-making tools. A major challenge is ensuring that AI solutions can seamlessly integrate with Türkiye's National Health Information System (e-Nabız), which serves as the central database for patient records. [75]

Another concern is unequal access to AI-driven healthcare solutions across different regions of Turkey. While metropolitan hospitals in cities like Istanbul, Ankara, and Izmir have started piloting AI-based decision support systems, hospitals in rural and underdeveloped regions often lack the necessary digital infrastructure, trained personnel, and computational resources to adopt AI solutions effectively. [76] This regional disparity raises concerns about healthcare equity, as patients in rural areas may not benefit from AI-driven innovations at the same rate as those in urban centers.

To overcome these barriers, Turkey must:

1. Develop a comprehensive AI regulatory framework tailored for medical applications.
2. Invest in nationwide AI training programs for healthcare professionals to bridge the expertise gap.
3. Strengthen AI integration in national health infrastructure, ensuring that AI-driven tools are compatible with existing hospital management systems.
4. Encourage public-private partnerships, leveraging collaborations between government agencies, academic institutions, and technology firms to accelerate AI adoption.

Despite these challenges, Turkey has significant potential for AI expansion in healthcare, particularly through its large-scale national health initiatives and increasing investment in digital health transformation. Addressing regulatory, infrastructural, and regional disparities will be crucial to ensuring equitable and efficient AI implementation in HIV care and beyond.

Conclusion and Future Perspectives

AI has emerged as a transformative force in the fight against HIV, revolutionizing diagnostic accuracy, treatment optimization, and public health strategies. AI-driven innovations, such as ML models and data analytics, have enabled early detection through biomarker analysis, optimized ART regimens, and facilitated personalized medicine by integrating pharmacogenomics and patient-specific data. Furthermore, AI-powered epidemiological models have enhanced the ability to predict and mitigate HIV transmission at the population level, ensuring more efficient resource allocation and targeted interventions.

Despite these promising advancements, challenges persist. Ethical concerns, including data privacy and algorithmic bias, need to be systematically addressed to ensure equitable healthcare delivery. Accessibility remains a significant hurdle, particularly in low-resource settings, where technological infrastructure and trained personnel may be limited. In addition, the integration of AI into healthcare systems requires robust regulatory frameworks, interdisciplinary collaboration, and sustained financial investment to ensure scalability and sustainability.

Future research should focus on refining AI algorithms to improve their interpretability, accuracy, and generalizability across diverse populations. Efforts must also be directed toward building inclusive datasets that minimize biases and reflect the demographics of those most affected by HIV. Collaborative initiatives between governments, private sectors, and non-governmental organizations (NGOs) can accelerate the global deployment of AI tools, particularly in regions with the highest HIV burdens.

As the capabilities of AI continue to expand, its role in combatting HIV is likely to evolve further. By embracing these technologies responsibly and ensuring that their benefits are distributed equitably, the global health community can make significant strides toward reducing new infections, improving the quality of life for those living with HIV, and ultimately achieving an AIDS-free generation

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