Utilization of Machine Learning Algorithms for the Strengthening of HIV Testing: A Systematic Review

P2 – I2

Musa Jaiteh[1], Edith Phalane[1], Yegnanew A. Shiferaw[2], Karen Alida Voet[3], Refilwe Nancy Phaswana-Mafuya[1]

[1]South African Medical Research Council/University of Johannesburg (SAMRC/UJ) Pan African Centre for Epidemics Research (PACER) Extramural Unit, Faculty of Health Sciences, Johannesburg, South Africa

[2]Department of Statistics, Faculty of Science, University of Johannesburg, Johannesburg, South Africa

[3]Department of International Health, Johns Hopkins University Bloomberg School of Public Health, Baltimore, USA

This study reviewed 845 articles, of which 51 eligible studies were analyzed. More than 75% of the articles were conducted in the Americas and Sub-Saharan Africa (SSA), and a few were from Europe, Asia, and Australia. The most common machine learning (ML) algorithms applied in HIV testing interventions were logistic regression, deep learning, support vector machine, random forest, extreme gradient booster, decision tree, and the least absolute shrinkage selection operator model. The findings demonstrate that ML techniques exhibit higher accuracy in predicting HIV risk/testing compared to traditional approaches.

BACKGROUND

- ❖ HIV testing is essential in identifying people living with HIV (PLHIV) and linking them to care, enabling them to attain suppressed viral loads [1,2].
- ❖ This aligns with the United Nations Program on HIV/AIDS (UNAIDS) 95-95-95 target to end HIV as an epidemic by 2025 [1].
- ❖ However, traditional HIV testing methods alone seem inadequate for the ambitious goal as HIV testing rates remain low in many countries due to apparent issues with accessibility, acceptability, and privacy [3].
- ❖ Therefore, there is a need to integrate innovative HIV testing approaches such as ML, which involves the use of computational and statistical algorithms that learn from data to improve the efficacy of predictions, and the quality of decisions compared to traditional methods (TM) [4].
- ❖ Several ML techniques have demonstrated efficacy in precisely forecasting HIV risk and identifying the most eligible individuals for HIV testing in various countries.
- ❖ Yet, there is a data gap on the utility of ML algorithms in strengthening HIV testing worldwide.
- ❖ This systematic review aimed to evaluate how effectively ML algorithms can enhance the efficiency and accuracy of HIV testing interventions and to identify key outcomes, successes, gaps, opportunities, and limitations in their implementation.

METHODS

- ❖The review was conducted from 20 September 2023 to 30 April 2024.
- ❖It was registered with the Protocol Review International Prospective Register of Systematic Reviews (PROSPERO) (ID: CRD42023464960).
- ❖ The systematic review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA, 2020) guidelines.
- ❖ A comprehensive literature search was conducted via PubMed, Google Scholar, Web of Science, Science Direct, Scopus, and Gale One-file databases using relevant keywords synonymous with "machine learning" AND "HIV testing."
- ❖ The Population, Intervention, Comparison, Outcome, and Study Design (PICOS) framework guided the selection of studies.
- ❖ Articles that were available in full-text, conducted between 2010 and 2024, in English, and among individuals aged 18 years and above were included.
- ❖ RefWorks and Covidence aided the entire review process.
- ❖ The results were narratively summarised, and a t-test was conducted to compare the accuracies of ML and TM.

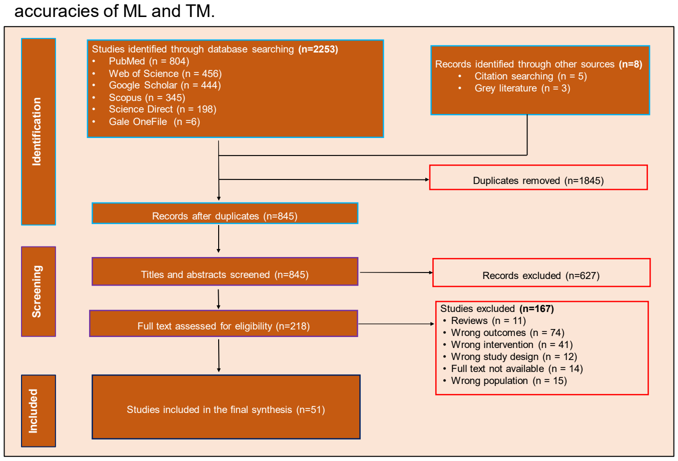

Figure 1. PRISMA flow chart representing the review selection process

RESULTS

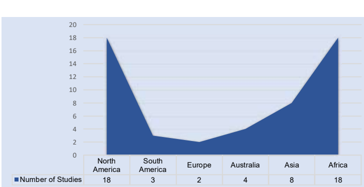

Figure 2. Distribution of HIV testing and machine learning studies by region

Table 1. Distribution of studies by country

Top 10 countries with a minimum number of 3 studies					
No.	Country	Number of Studies	No.	Country	Number of Studies
1	USA	18	6	South Africa	3
2	China	5	7	Tanzania	3
3	Zimbabwe	5	8	Kenya	3
4	Ethiopia	5	9	Zambia	3
5	Australia	4	10	Malawi	3

RESULTS CONTINUED

Table 2. Most frequently utilized machine learning algorithms

ML algorithms	No. of Studies	Largest dataset size	Best performance / Reference
LR	19	4,348,178	• 90.5% highest accuracy • Best model in 2 studies
RF	15	4,348,178	• 94.4% highest accuracy • Best model in 5 studies
SVM	13	124,777	• 95.1% highest accuracy • Best model in 1 study
XGBoost	9	124,777	• 99% highest sensitivity • Best model in 5 studies
DL models (ANN, RNN, CNN, LSTM)	9	88,642	• 98% highest accuracy • Best model in 3 studies
LASSO model	7	4,348,178	• 82% highest accuracy
DT	7	56,682	• 81.9% highest accuracy • Best model in 1 study
KNN	6	6,672	• 80% highest accuracy

Table 3. Machine learning interventions employed to enhance HIV testing

Themes	Intervention & Key Outcomes
Innovative/ Accurate HIV testing / Diagnostic Accuracy	Developed ML conversational agents for automated self-HIV counseling and testing, providing a natural and comfortable experience.
	Compared ML and traditional testing, revealing that ML consistently outperformed traditional methods in HIV diagnosis prediction.
	Focused on improving HIV accuracy testing using ML, achieving 83% accuracy with RNN models.
	Used ML to improve HIV diagnostic accuracy & reduce false positives
	Utilized ML to identify HIV risk factors, including socio-behavioural factors, biomarkers, and demographic variables
Predicting HIV testing/ Risk/ Status	Applied ML algorithms to predict HIV status increasing predictive performance and suggesting the need to test 384 individuals to find one undiagnosed person with HIV.
	Applied ML for predicting HIV status and improving testing capacity among specific populations (MSM)
	Identified predictors of HIV risk and uptake of HIV self-testing (HIVST) among MSM, emphasizing the accuracy and efficiency of ML models.
Efficiency and Prioritization in Testing	Improved efficiency in HIV testing by classifying high risk HIV individuals
	Developed models to predict incident HIV diagnoses effectively
	Used ML to enhance the efficiency of diagnostic tools.

Note: LR, Logistic regression; RF, random forest; SVM, support vector machine; XGBoost, extreme gradient boosting; DL, deep learning; ANN, artificial neural network; RNN, recurrent neural network; CNN, convolutional neural network; LSTM, long–short-term memory; LASSO, least absolute shrinkage and selection operator; DT, decision tree; KNN, K-nearest neighbor; ML, machine learning; MSM, men who have sex with men.

Table 4. Empirical differences between machine learning and traditional methods in HIV testing predictive modeling

Studies	Traditional Methods	Machine learning	Outcome
Roche et al. (2024)	Human Interpretation of HIVST	AI algorithm interpretation of HIVST	• Humans are more likely to correctly interpret true positive HIV test results (PPV=100%) compared to the AI algorithm (PPV=82%) • AI algorithm (NPV-100%) is more likely to correctly interpret true negatives in comparison to humans (NPV-99.9%)
Ni et al. (2024)	Human and Empirical models	ML models	• The ML model motivated more alters to conduct HIVST • The difference between the ML model and the empirical scale was not significant
Jing et al. (2023)	Human	ML models	• ML model outperformed human identifications and distribution of HIVST kits • The ML approach increased HIVST kit distribution by 18%
He et al. (2022)	TM	ML models	• The ML models outperformed TM in HIV risk prediction among MSM • ML achieved 94% accuracy
Jing et al. (2021)	TM	ML	• The ML method outperformed the TM • The ML method increased the economic benefits of HIVST kit distribution by more than 23%
Bao et al. (2021)	TM	ML	• The ML models consistently outperformed the TM • The ML achieved an accuracy of 76.3% compared to TM (68%)
Oladokun et al. (2019)	TM	ML	• The TM outperformed the ML model • Both models did not achieve high accuracy
Rice et al. (2018)	TM	ML	• The ML model outperformed the TM • HIV testing was increased by 18.8% in the AI group compared to the comparison group (8.1%)
Balzer et al. (2020)	TM	ML	• ML outperformed TM • ML model achieved an accuracy of 78% compared to TM (68%)
Conclusion	TM outperformed ML in only two studies	ML outperformed TM in seven studies	• ML models outperform TM methods based on the empirical evidence from the study's sample

Note: TM, traditional methods; ML, machine learning; AI, artificial intelligence; HIVST, HIV self-test; PPV, positive predictive value; NPV, negative predictive value.

Table 5. T-test results of the comparison between traditional and machine learning

Predictive Model	Studies	Mean	Std. Err	Std. Dev	95% CI
Machine Learning	35	86.66	1.79	10.61	82.01-89.03
Traditional Method	8	73.13	2.29	6.47	67.72-78.54
Combined Values	43	83.33	1.69	11.07	79.92-87.73
Difference in Values		12.53 (p =0.0002)	2.91		6.39-18.66

CONCLUSION

- ❖ This study points to the positive impact of ML in enhancing early prediction of HIV spread, optimizing HIV testing approaches, improving efficiency, and ultimately enhancing the accuracy of HIV diagnosis.
- ❖ The study further reveals that ML techniques are more accurate than traditional approaches in predicting HIV risk, testing, and status.
- ❖ Also, most ML interventions are concentrated in developed countries due to a lack of expertise and the inapplicability of models in under-resourced countries.
- ❖ Research institutions should train more HIV epidemiologists to become ML experts.
- ❖ Screening programs should incorporate automated HIV testing models for improved privacy, acceptability, and accessibility with high diagnostic accuracy.

FUNDING

The work reported herein was made possible through funding by the South African Medical Research Council (SAMRC) through its Division of Research Capacity Development under the Mid-Career Scientist Program using funding received from the South African National Treasury (Project Code number: 57035 [SAMRC File ref no: HDID8528/KR/202]). This work was conducted under the guidance of SAMRC/University of Johannesburg (UJ) Pan African Centre for Epidemics Research (PACER) Extramural Unit. The content herein is the authors' sole responsibility and does not necessarily represent the official views of SAMRC or UJ. This paper also forms part of a PhD study by Mr Musa Jaiteh, whose studies are funded by the Global Excellence Stature (GES) 4.0 Scholarship at UJ.

ACKNOWLEDGMENTS

The authors would like to thank the SAMRC/UJ PACER Extramural Unit and the UJ GES 4.0 Scholarship for funding this study. I also thank the SAMRC/UJ PACER Extramural Unit for sponsoring the attendance of the WCE conference. My sincere appreciation goes to Ms Rathaba Dikomo, a UJ Librarian, for providing training on database search and Covidence software.

SELECTED REFERENCES

1. World Health Organization. Consolidated Guidelines on HIV Prevention, Testing, Treatment, Service Delivery, and Monitoring: Recommendations for a Public Health Approach. 2021. Available online: https://www.who.int/publications/i/item/9789240031593 (accessed on 17 February 2024).
2. UNAIDS. *FACT SHEET 2023 Global HIV Statistics People Living with HIV People Living with HIV Accessing Antiretroviral Therapy New HIV Infections AIDS-Related Deaths Key Populations*; UNAIDS: Geneva, Switzerland, 2023.
3. Mannoh, I.; Amundsen, D.; Turpin, G.; Lyons, C.E.; Viswasam, N.; Hahn, E.; Ryan, S.; Baral, S.; Hansoti, B. A Systematic Review of HIV Testing Implementation Strategies in Sub-Saharan African Countries. *AIDS Behav.* **2022**, *26*, 1660–1671. https://doi.org/10.1007/s10461-021-03518-z.

AUTHOR'S CONTACT INFORMATION

mjaiteh1993@gmail.com/ musaj@uj.ac.za

+27791850627

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WORLD CONGRESS OF EPIDEMIOLOGY 2024