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Identifying an Emerging HIV Epidemic in Punjab, Pakistan: Forecasting Trends using Prophet Model and Classical ARIMA Model (2020–2025)

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Abstract

Background: Pakistan has witnessed concerning shifts in HIV epidemic especially in Punjab, where HIV and AIDS incidence continues to rise. This study compares the predictive accuracy of the Prophet model, machine learning model with classical ARIMA configurations for monthly HIV and AIDS case forecasting in Punjab. **Methods:** Monthly surveillance data (January 2020–October 2025) from Punjab AIDS Control Program (PACP) was used to train and validate Prophet and multiple ARIMA models. The modelling performance was assessed using RMSE, MAE, MAPE, BIC and also Ljung Box Q tests. Forward forecasts were generated for HIV reactive and AIDS (CD4 < 200) cases through 2026. **Results:** Machine learning model (Prophet) outperformed all ARIMA models in forecasting HIV reactive cases by achieving the lowest RMSE (132.6) and MAPE (16.4%), for AIDS cases projection, all models exhibited high error rates (Prophet MAPE > 300%) with ARIMA $(0,1,0)(0,1,1)_{12}$ better performance (MAPE ~174%). Forecasted outputs estimates approximately 8,490 new HIV cases in 2026 with uncertainty bounds reaching nearly 15,000 cases, indicating a continued upward trajectory and for AIDS the count in 2026 may rise to 25,596 new cases, thou, forecasting AIDS remains a challenge. The results demonstrate superior ability of Prophet model to capture non-linear trends and seasonality in HIV surveillance data. **Conclusion:** Prophet model superior performance reflects its ability to model nonlinear and seasonally irregular HIV surveillance data. Integration of machine learning techniques such as Prophet model into provincial HIV programs can enhance planning and accelerate progress toward achieving UNAIDS 95-95-95 targets.

Key Words: HIV Infections, epidemiology, AIDS, Forecasting, Machine Learning, ARIMA, SARIMA, Public Health Surveillance, Pakistan, Prophet Model

Introduction

HIV is a global epidemic which has reported 40.1 million deaths worldwide (Payagala et al., n.d.). While ART has reduced AIDS-related mortality, the decline in new HIV infections has been disproportionate particularly in countries like Pakistan, where the epidemic has shifted from low prevalence to concentrated levels (Orlando et al., 2025). In Punjab, high-risk behaviors, underreporting delayed diagnosis and stigma exacerbate the situation, leading to a rapid rise in HIV and AIDS cases (Zubair et al., 2025). Multiple factors contribute including delayed diagnosis or high-risk behavioral practices, underreporting, health system fragmentation and stigmatization among key populations continue to influence the transmission (Hamid Khan et al., 2026). Surveillance data from the Punjab AIDS control program reveals increasing HIV and AIDS cases with fluctuations in detection patterns due to factors like improved diagnostic facilities and health system responses. However, the challenge remains in forecasting future trends particularly in the given irregular patterns of HIV transmission in Punjab (Abdullah et al., 2021a). This study aims to bridge this gap by comparing the performance of the Prophet machine learning model with classical ARIMA models in forecasting HIV and AIDS cases.

Forecasting infectious diseases is of true epidemiological importance where incidence patterns are changing rapidly and where healthcare systems must remain prepared for shifts in disease burden (Rahman et al., n.d.)(Hamid Khan et al., n.d.). While traditional ARIMA models have been widely used in infectious diseases forecasting and their reliance on linear assumptions limits their ability to capture abrupt changes or irregular seasonal patterns often seen in HIV surveillance data. Recent studies have demonstrated that Prophet model has non-linear dynamics more effectively that makes this model an effective tool to capture forecasting trends in HIV and AIDS in Punjab for more accurate predictions for HIV surveillance (Karasinghe et al., 2024; Siamba et al., 2023).

ARIMA models generate autoregressive patterns, differencing to remove non-stationarity or moving average components in the time dependent datasets. Seasonal ARIMA (SARIMA) is an extension that allow incorporation of seasonality by making the model suitable for surveillance datasets with cyclic fluctuations (Arumugam et al., n.d.).

Hybrid models such as combining ARIMA and Prophet can outperform single models for HIV/AIDS forecasting. Recent studies show that combining SARIMA and Prophet improves predictive accuracy for AIDS incidence compared with single models which suggest hybrid models can better capture linear as well as non-linear dynamics in disease data. (Luo et al., 2022)

HIV surveillance data in Pakistan deviates from linear assumptions due to abrupt increases in case reporting or screening campaigns, making machine-learning based models like Prophet more suitable for capturing these irregular patterns (Aizaz et al., 2023; Rabold et al., n.d.). Prophet model developed by Meta which was formerly Facebook that offers design to accommodate abrupt trend changes, irregular seasonality, missing observations and also holiday effects properties particularly relevant to real time public health datasets(Chitwadgi, 2024)(Rafferty, 2023). Despite its growing application in health forecasting globally, Prophet has not been rigorously evaluated for forecasting in comparison to traditional ARIMA models using HIV surveillance data (Ghanem, 2025; Sardar et al., 2023). The lack of predictive modelling evidence poses challenges for health authorities who require correct projections of HIV and AIDS to plan testing expansion which is much needed or ART centers distribution(Chen et al., 2024).

This study applies Prophet and multiple ARIMA configurations to monthly reported HIV reactive and AIDS cases from January 2020 to October 2025 across all the districts of Punjab. By applying two distinct models either classical time series modelling and machine learning based forecasting, this study offers a comprehensive assessment of predictive capacity for HIV surveillance in a rapidly evolving epidemic context in Punjab, Pakistan. The modelling framework incorporates stationarity testing, autocorrelation assessment, model fitting, cross-metric comparison, and forward forecasting to evaluate which approach provides more reliable projections. The findings provide timely evidence for predictive analytics to support provincial HIV control strategies, enabling health policymakers to anticipate caseload progression, strengthen resource deployment, and develop targeted programming driven by data rather than reactive response.

Methodology

Data Collection

The data for this study were collected from monthly records of Punjab AIDS Control Program of the entire districts of Punjab, Pakistan. The data consists of the total number of monthly reported HIV and AIDS cases in Punjab from January 2020 to October 2025. The study is related to time series forecasting and modelling of reported HIV and AIDS cases. The data has been gathered from the Punjab AIDS Control Program. The monthly reported cases of HIV and AIDS in Pakistan from 2020 to 2025 reveal a steadily increasing trend, both in disease burden and treatment coverage. For HIV and AIDS cases, the average number of monthly cases have begun from 278 and zero, respectively in January 2020 to 983 and 60 for HIV and AIDS respectively in October 2025. Reportedly, the cumulative incidence of HIV in Punjab was 64455 and 34221 for AIDS with median of 728 and maximum of 10509 cases.

These statistics confirm the upward trend and reflect increased case identification. The forecasting equations used in forecasting models will be statistical functions utilized to predict the unpredictable behavior of a phenomenon, which aids in decision-making.

By analyzing historical data patterns, these models generate predictions that inform decision-making processes across various fields, including public health. For instance, in the context of HIV and AIDS, time series forecasting can help predict future case trends and treatment needs, enabling healthcare planners to allocate resources effectively and implement timely interventions.

The models make use of past information to understand forecasting behavior. The dataset was actually examined for all kinds of missing values, outliers or variance instability. Seasonal decomposition using STL and stationarity testing through Augmented Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) were performed to confirm the need for differencing and seasonal components in datasets as illustrated in flowchart in **figure 1.** The ADF test for HIV showed p value=0.02, indicating need for differencing to achieve stationarity whereas, KPSS test had p value=0.03, confirming non-stationarity. Similarly for AIDS KPSS p-value=0.12, indicating stationarity so no differencing was applied. HIV data was differenced while AIDS data remained unchanged.

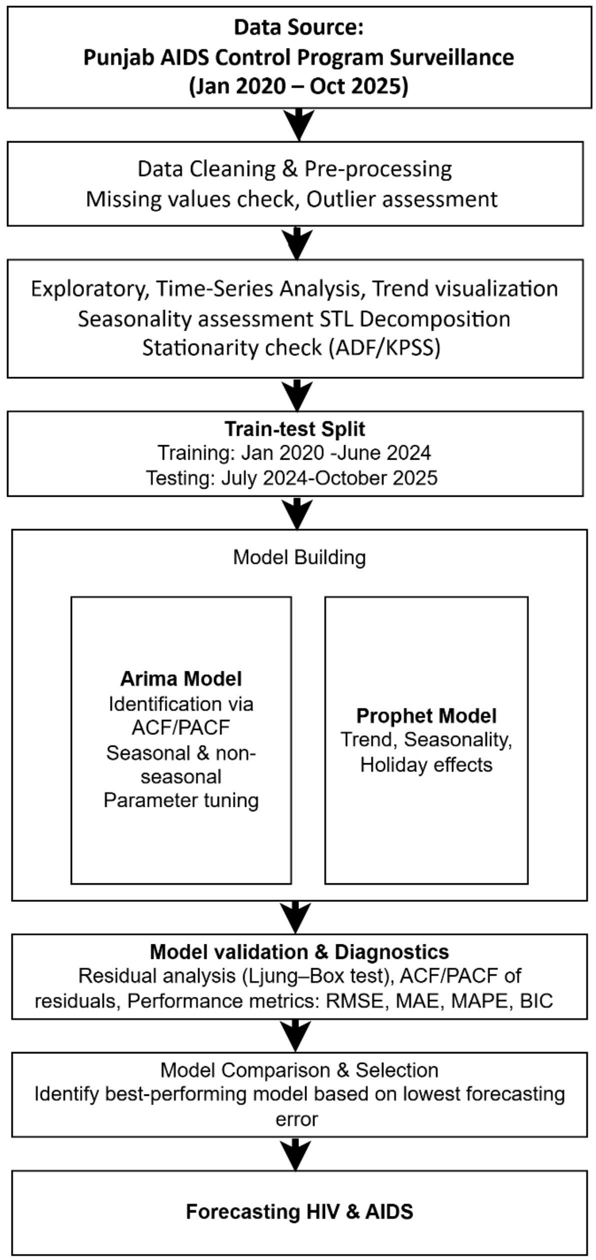

Figure 1: Flowchart outlining the methodological framework for forecasting HIV and AIDS cases in Punjab, Pakistan, using monthly surveillance data (Jan 2020 – Oct 2025).

ARIMA Models

Several variations of the **AutoRegressive Integrated Moving Average (ARIMA)** model were applied, each with different combinations of autoregressive (AR), differencing (I), and moving average (MA) components. ARIMA models are particularly useful for time series data with trends and seasonal effects. The models tested include ARIMA(1, 1, 0)×$(0, 1, 1)_{12}$ for seasonal ARIMA model with one autoregressive term and one seasonal moving average term. ARIMA(0, 1, 1)×$(0, 1, 1)_{12}$ was for another seasonal ARIMA variant with different combinations of AR and MA terms. Whereas, ARIMA(1, 1, 1)×$(0, 1, 1)_{12}$ were more complex ARIMA model with both autoregressive and

moving average components and ARIMA(1, 1, 0)×(0, 1, 0)$_{12}$, ARIMA(0, 1, 1)×(0, 1, 0)$_{12}$ models did not include seasonal adjustments for the moving average terms but were tested to capture any trends in the data.
The ARIMA(p, d, q) model is generally represented as:

$$Y\_t = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + ... + \varphi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta\_q \varepsilon_{t-k} + \varepsilon_t$$

Where: Y_t is the value of the time series at time t, μ is the constant term (mean), $\varphi_1, \varphi_2, ..., \varphi_p$ are the autoregressive (AR) coefficients, $\theta_1, \theta_2, ..., \theta_k$ are the moving average (MA) coefficients, ε_t is the white noise (residuals) at time t, p, d, and q are the order of the AR, differencing, and MA terms respectively.
The equation for a seasonal ARIMA model can be written as:

$$(1 - \varphi_1 B - ... - \varphi_p B^p) (1 - B^p)^d Y_t = (1 + \theta_1 B + ... + \theta_k B^k) \varepsilon_t$$

Where: $\varphi_1, ..., \varphi_p$ are the AR parameters, $\theta_1, ..., \theta_k$ are the MA parameters, d is the differencing order, p is the seasonality period (e.g., 12 for monthly data).

Machine Learning (Prophet Model)

The Prophet model was employed for time series forecasting. Prophet is known for its ability to handle seasonal patterns, holidays, and missing data, making it suitable for forecasting disease-related trends in healthcare. Initially, model training was carried out using training set that included data from January 2020 to October 2025 of monthly datasets.
The dataset was split into a training set (January 2020–June 2024) and a testing/validation set (July 2024–October 2025) to evaluate predictive performance on unseen data.
Then, Prophet automatically detected seasonality effects and holidays, allowing it to forecast future cases with adjustments for recurring trends. The trained model was used to forecast HIV Reactive and AIDS cases for future months, specifically from November 2025 onwards, through October 2025.
The Prophet model uses an additive model with a trend, seasonality, and holidays to forecast time series. The formula is:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

Where: y(t) is the observed time series at time t, g(t) is the trend function, typically modeled as a piecewise linear or logistic growth, s(t) is the seasonal component, modeled as a Fourier series, h(t) is the holiday effect, ε_t is the error term.

The trend function g(t) can be defined as:

$$g(t) = \text{logistic growth model: } \frac{C}{1+\exp\left(-k(t-to)\right)}$$

Where: C is the carrying capacity (upper bound), k is the growth rate, t_0 is the time of the maximum growth rate.

The seasonal component s(t) can be represented as:

$$s(t) = \sum_{i-1}^{k} a_i \cos(2\pi f_i t + \varphi_i)$$

Where; a_i are the amplitude coefficients, f_i are the frequencies of the seasonal patterns, φ_i are the phase shifts.
The model's performance was evaluated using several metrics like RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). These metrics helped assess the model's accuracy and error rate.
For all models, the following error metrics are used to assess the forecast accuracy:

RMSE (Root Mean Square Error):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

Where; y_t is the actual observed value at time t, $\hat{y}_t$ is the predicted value at time t, n is the number of observations.
MAE (Mean Absolute Error):

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|$$

MAPE (Mean Absolute Percentage Error):

$$\mathbf{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

The Ljung-Box test is used to check if the residuals from the model are white noise. The test statistic is given by:

$$\mathbf{Q = n(n+2)} \sum_{k=1}^{m} \left| \frac{\hat{\rho}^2(k)}{n-k} \right|$$

Where; n is the number of observations, m is the number of lags to check, ρ̂(k) is the sample autocorrelation at lag k. Prophet Model is semi-parametric addictive model that combines both parametric and non-parametric components for seasonality. Unlike the traditional machine learning models that require large datasets, Prophet can effectively handle time series data with irregular seasonality, missing values and large outliers. It is flexible due to which it captures trends and seasonal patterns without needing extensive data like LSTM networks.

The data was tested for stationarity, and differencing was applied if necessary to stabilize the series. ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots were used to identify the optimal order of the AR and MA terms. Once the appropriate parameters were selected, the ARIMA models were fitted to the data, and forecasts were made for the future months. Forecasting accuracy was quantified and trained by comparison between two models from dataset and illustrated in Figure 2.

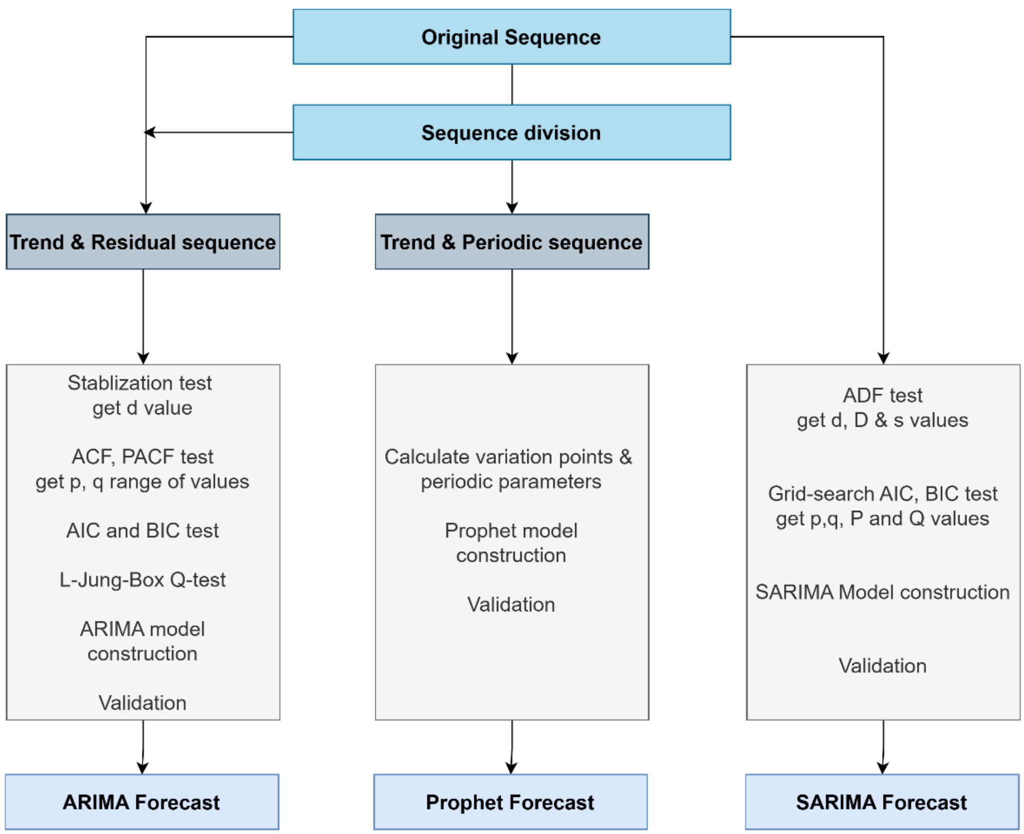

Figure 2: Flowchart depicting the forecasting workflow for HIV and AIDS cases using three modeling approaches against ARIMA, Prophet, and SARIMA

Results

Forecasting accuracy of HIV and AIDS cases were assessed using RMSE, MAE and MAPE across Machine learning Prophet and various ARIMA configurations. Overall, the Prophet model demonstrated superior predictive performance for HIV reactive cases as well as AIDS cases.

HIV Reactive Cases Forecasts

The Prophet achieved the lowest forecasting error for HIV reactive cases with MAPE of 16.4% outperforming all ARIMA models showing RMSE (Root Mean Square Error) 132.646 and MAE (Mean Absolute Error) 118.974. The comparison around monthly datasets from 2020 to 2025 that Prophet model closely tracks actual trends and exhibits better alignment with recent variations.

The ARIMA (1, 1, 0)×(0, 1, 1)$_{12}$ model that commonly used seasonal ARIMA model, had an RMSE of 186.975, a MAE of 158.386, and a MAPE of 23.302%. This shows a higher error rate compared to Prophet, indicating that Prophet was more accurate in capturing trends and seasonality. Other ARIMA models illustrated in Table: 1. Ljung-Box test values show residuals are mostly white noise across models, strengthening model validity.

Table 1: Performance comparison of Prophet and seasonal ARIMA models in forecasting HIV reactive cases in Punjab

Model	RMSE	MAPE	MAE	BIC	Ljung-Box Q (18)	Sig.
Prophet	132.646	16.438	118.974		9.653	0.562
ARIMA(1, 1, 0) x 0, 1, 1)$_{12}$	186.975	23.302	158.386	643.923	15.758	0.15
ARIMA(0, 1, 1) x **(0, 1, 1)**$_{12}$	**209.511**	**25.805**	**174.136**	**634.375**	**14.126**	**0.226**
ARIMA(1, 1, 1) x **(0, 1, 1)**$_{12}$	**214.79**	**26.637**	**179.796**	**635.554**	**10.387**	**0.496**
ARIMA(1, 1, 0) x (0, 1, 0)$_{12}$	215.382	22.862	160.92	648.652	15.683	0.153
ARIMA(0, 1, 1) x (0, 1, 0)$_{12}$	220.08	23.576	165.099	639.066	9.725	0.555
ARIMA(1, 1, 1) x (0, 1, 0)$_{12}$	225.989	24.421	170.031	641.138	7.238	0.779
ARIMA(0, 1, 0) x (0, 1, 1)$_{12}$	270.37	35.245	241.931	644.92	8.983	0.623
ARIMA(0, 1, 0) x (0, 1, 0)$_{12}$	296.111	34.21	234.667	653.381	10.793	0.461

From January 2020 to October 2025, approximately 64,455 individuals have screened HIV-reactive in Punjab, with annual confirmed case counts showing persistent transmission: 21,271 cases in 2020, 8,026 in 2021, 8,185 in 2022, 10,212 in 2023, 9,224 in 2024, and 7,537 cases already recorded by October 2025. The **figure 3** also indicates a sustained and concerning upward trend throughout the year from 2020-2025 since this screening initiative began in 2020 in Punjab. This make the cumulative incidence of 64455 in Punjab.

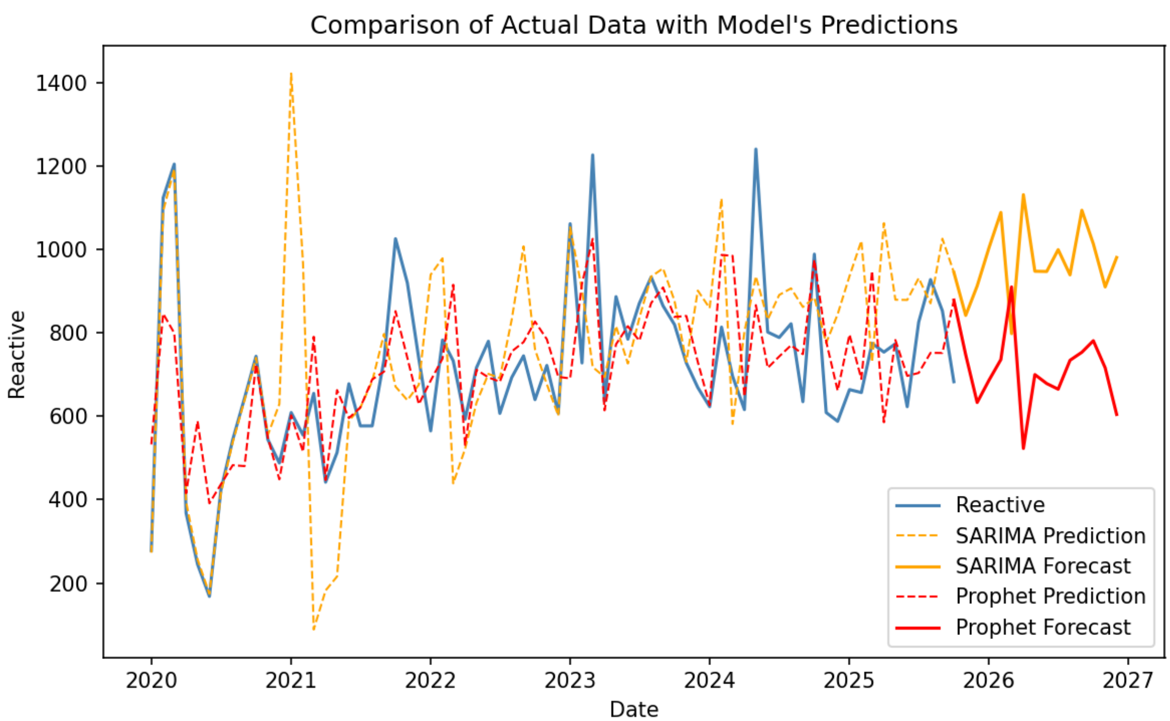

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Figure 3: Comparison of SARIMA and Prophet model for HIV Reactive cases

AIDS ($CD4^+$ count) forecasts

For AIDS-related cases, regularly AIDS testing was performed of the HIV patients and those having $CD4^+$ count less than 200 depicts disease severity and burden to healthcare was identified using comparison of Machione learning and conventional ARIMA where Prophet again showed good performance than ARIMA models but had higher error metrics compared to HIV reactive cases having RMSE 781.414, MAE 712.822 and MAPE of 317.261%, In contrast, the ARIMA (0, 1, 0)×(0, 1, 1)$_{12}$ model had an RMSE of 534.134 and a MAPE of 173.832%, indicating that while Prophet was still more accurate, both models exhibited higher errors in forecasting AIDS cases illustrated in Table 2 and the comparison is depicted in figure 4.

Table 2: Performance comparison of Prophet and seasonal ARIMA models in forecasting AIDS cases in Punjab

Model	RMSE	MAPE	MAE	BIC	Ljung-Box Q(18)	Sig.
Prophet	781.414	317.261	712.822		10.798	0.29
ARIMA (0, 1, 0) x (0, 1, 1)$_{12}$	**534.134**	**173.832**	**431.941**	**660.217**	**11.483**	**0.404**
ARIMA (0, 1, 1) x (0, 1, 1)$_{12}$	542.283	181.174	451.868	663.286	7.955	0.717
ARIMA (1, 1, 0) x (0, 1, 1)$_{12}$	542.772	181.194	452.433	663.265	7.71	0.739
ARIMA (1, 1, 1) x (0, 1, 1)$_{12}$	562.427	190.87	497.324	664.35	6.794	0.816
ARIMA (0, 1, 0) x (0, 1, 0)$_{12}$	1084.439	338.156	883.5	669.254	14.357	0.214
ARIMA (0, 1, 1) x (0, 1, 0)$_{12}$	1094.631	341.455	894.398	672.787	12.235	0.346
ARIMA (1, 1, 0) x (0, 1, 0)$_{12}$	1096.979	342.221	896.977	672.724	11.726	0.385
ARIMA (1, 1, 1) x (0, 1, 0)$_{12}$	1144.261	354.537	950.477	674.101	9.844	0.544

AIDS cases, representing advanced disease progression show a deeply concerning pattern in Punjab. From January 2020 to October 2025 that makes cumulative incidence of 34,221 that individuals have been diagnosed with AIDS. Annual case detection fluctuated but remained unacceptably very high with 304 cases in 2020 since it was the beginning of the program initiative then it goes to 2017 cases of AIDS in 2021, 10,724 in 2022, 1,174 in 2023, 11,161 in 2024, and 8,840 cases already reported by October 2025 illustrated in figure 4. These figures reflect delayed diagnosis, late treatment initiation, and gaps in routine monitoring and various other factors.

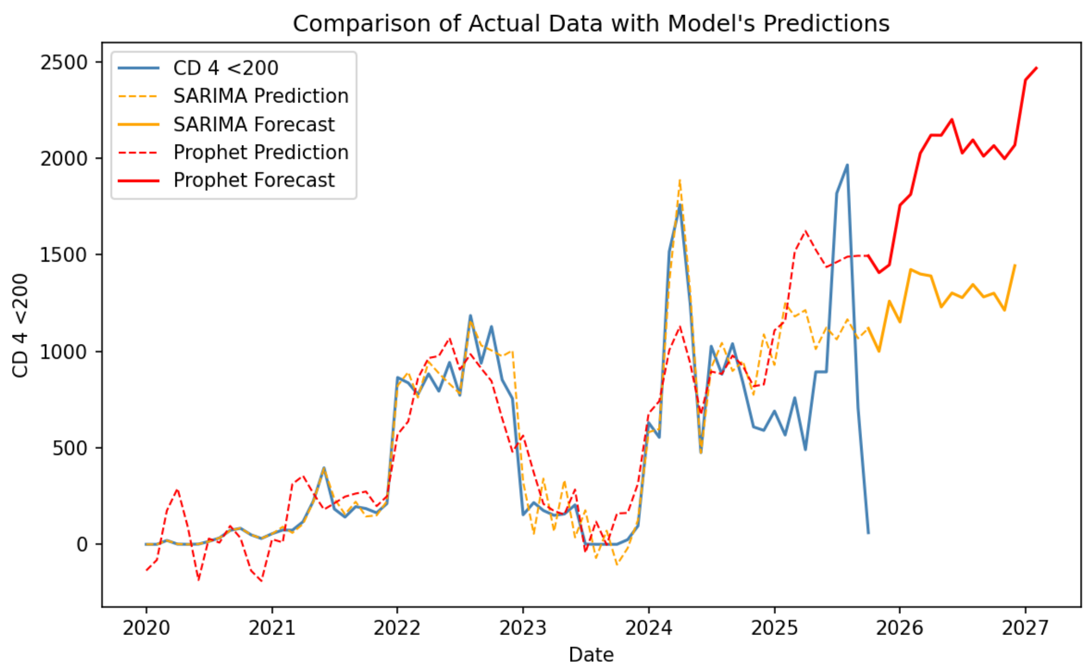

Figure 4: Comparison of SARIMA and Prophet model for AIDS ($CD4^{+}$ cases)

The MAPE values of AIDS case forecasting remained significantly high (MAPE> 300%) indicated metric instability. This issue arised because MAPE is sensitive to low count data, which remained common in reporting of AIDS cases. MAPE produced distorted evaluations due to large errors, therefore, sMAPE (symmetric mean absolute percentage error) was used, which is better suited for sparse data as it balances errors symmetrically and avoids the extreme sensitivity of MAPE that is rather reliable for evaluating forecast performance. Since, sMAPE considers both forecast and actual value in denominator and both use different approach to handle data. Therefore, Prophet model achieved sMAPE 28.3%, significantly lower than sMAPE 47.6% obtained for ARIMA model. Therefore, Prophet model effectively captures the underlying patterns in AIDS case reporting, despite irregularities in data. The lower sMAPE value conforms Prophet model to be reliable forecast for AIDS.

Temporal trends and forecasted cases.

HIV Reactive cases projections
The forecasts predict an increase in HIV Reactive cases over the forecast period, with seasonal fluctuations captured by the Prophet, Machine learning. While the growth in HIV Reactive cases is not drastic, it indicates the need for continued surveillance and healthcare planning to manage the disease burden effectively. Forecasted HIV cases gradually rise from ~687 in January 2026 to a peak of 910 in March, followed by fluctuations through December illustrated in Table 3.

Table 3: Forecasted monthly HIV cases in Punjab of the year 2026 using the Prophet model at 95% confidence intervals

Date	Forecasted HIV cases	Lower 95% CI	Upper 95% CI
01/01/2026	686.6326	294.3761	1114.731
01/02/2026	736.0968	277.6312	1195.734
01/03/2026	910.3771	472.241	1399.588
01/04/2026	522.9	56.11404	1047.221
01/05/2026	700.0812	195.7885	1288.658
01/06/2026	678.579	158.0174	1246.232
01/07/2026	665.0062	118.6351	1269.13
01/08/2026	734.3937	176.6673	1401.965
01/09/2026	753.6661	178.2586	1452.367
01/10/2026	781.3506	132.348	1497.942
01/11/2026	716.3757	16.7148	1483.699
01/12/2026	604.4938	62.7413	1432.646

Forecasting analysis estimates about 8,490 new HIV cases in Punjab in 2026, with upper uncertainty bounds reaching till nearly 15,000 cases at the 95% confidence interval illustrated in figure 5. Such projections indicate a potential shift toward an endemic trajectory if timely prevention and intervention measures are not strengthened. This wide prediction interval that reflects substantial uncertainty in monthly cases that align with the non-linear and interruption prone nature of HIV testing patterns in Punjab.

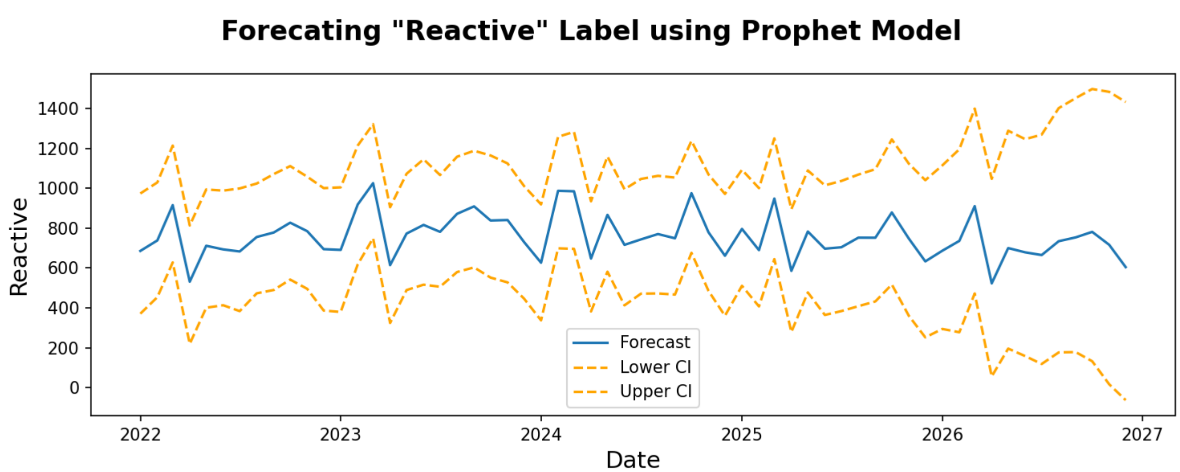

Figure 5: Prophet model-based forecast of monthly HIV reactive cases in Punjab, Pakistan.

AIDS Cases (CD4 < 200) cases projections
The forecast for AIDS-related cases shows a **gradual rise**, with a higher degree of uncertainty in the predictions. The larger MAPE and RMSE values suggest that this dataset may require additional modeling techniques or interventions,

such as considering demographic shifts, healthcare policies, or treatment advancements, to reduce prediction error but remains a challenge.

Lower bounds for AIDS forecasts dipped to zero for four months, underlining data unreliability. AIDS forecasts had confidence intervals as wide as 5,000 cases illustrated in Figure 6 that occasionally approach zero and upper bounds exceeding several thousand cases.

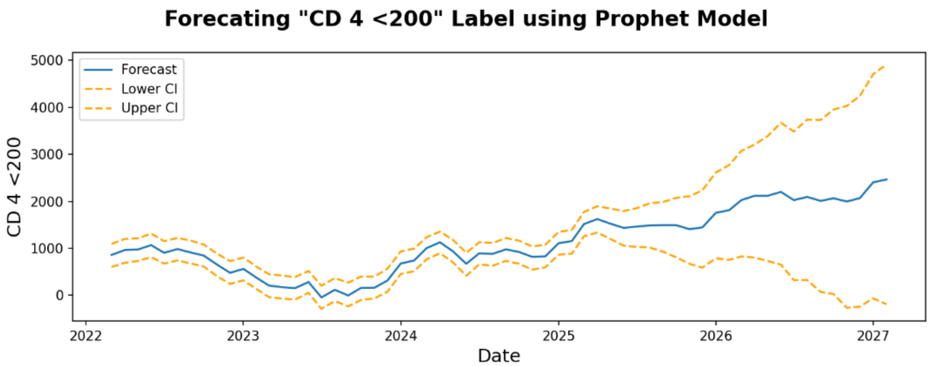

Figure 6: Prophet model based forecast of monthly AIDS ($CD4^+$ count) cases in Punjab, Pakistan.

The pattern likely reflect delayed presentation and inconsistent $CD4^+$ count testing availability and the sporadic diagnostic capture of advanced HIV cases all of which weaken predictive stability. The upper confidence limits in table 4 suggest that under certain conditions the healthcare system could face substantial increases in late-stage presentations whereas, lower bounds have vulnerability to under-diagnosis rather than true declines in AIDS incidence.

The forecasts for AIDS cases (CD4 <200), representing advanced disease progression that demonstrates a sharp rise throughout the projection period. Unlike HIV reactive cases, the projection of AIDS show larger variability and wider confidence bands that reflect inconsistent diagnostic capture and delayed health seeking behavior. Forecasted AIDS cases begin at approximately 2,025 in January 2026 and increase gradually across subsequent months with fluctuations sustained through December, as summarized in Table 4.

Table 4: Forecasted monthly AIDS cases in Punjab of the year 2026 using the Prophet model at 95% confidence intervals

Date	**Forecasted AIDS cases**	**Lower 95% CI**	**Upper 95% CI**
01/01/2026	2025.477	827.7270287	3072.067523
01/02/2026	2119.172	802.7449474	3210.336532
01/03/2026	2118.551	730.9055294	3387.627176
01/04/2026	2200.741	654.1094059	3671.24352
01/05/2026	2026.194	322.8293831	3486.560015
01/06/2026	2094.695	325.9755081	3740.325437
01/07/2026	2010.064	73.98554777	3731.367083
01/08/2026	2064.984	28.67339105	3952.796159
01/09/2026	1997.083	0	4031.000503
01/10/2026	2068.158	0	4244.314091
01/11/2026	2405.215	0	4705.60941
01/12/2026	2466.004	0	4913.579234

Forecasting analysis estimates approximately 25,596 new AIDS cases in Punjab during 2026 with the upper uncertainty limits that may reach as high as 46,146 cases in 2026 at the 95% confidence interval, as illustrated in Figure 6. The wide prediction span underscores serious instability in late-stage HIV detection trends and reflects

interruptions among care-seekers and uneven $CD4^{+}$ count testing access and delayed diagnosis in the region. Such projections strengthen warnings of a progressing endemic pattern and highlight the urgent necessity for enhanced continuous screening, early ART initiation, and more robust surveillance and follow-up systems.
Zero-floor correction or truncating negative values to zero is approach in epidemiology to ensure non-negative data in disease cases to prevent unrealistic negative predictions in models for certain forecasted values were generated in September to December due to high variability or low counts of identified AIDS individuals which is common in early stages of epidemic.

Discussion:
This study has evaluated the comparative forecasting performance of Prophet model and multiple ARIMA configurations in predicting HIV reactive cases and AIDS number of cases in Punjab, Pakistan, using monthly surveillance data from January 2020 to October 2025 obtained from Punjab AIDS control program. Using six years of provincial surveillance data, this study found that both Prophet (a decomposable additive model) and ARIMA (linear time-series models) can be fitted into the HIV and AIDS case trends in Punjab.
Based on the comparative modelling results among machine learning, Prophet consistently demonstrated superior predictive performance for monthly HIV reactive cases by achieving the lowest RMSE (132.6), MAE (118.97), and MAPE (16.4%) among all tested configurations. In contrast, the best-performing ARIMA model yielded noticeably higher error values (RMSE 186.98, MAE 158.39, MAPE 23.30%). These findings indicate that the Prophet model provided more reliable short-term forecasts,
For AIDS case forecasts all models had to struggle with Prophet model forecasts had especially high uncertainty like MAPE > 300% and even the best ARIMA model had very large errors like MAPE was about 174%. Interestingly, the simplest seasonal ARIMA $(0,1,0)(0,1,1)_{12}$ slightly outperformed Prophet on the AIDS data in terms of error rates, but both approaches did not show accuracy in predicting advanced cases. This diversity between HIV and AIDS results underscores that while Prophet model flexibility offers clear advantages for epidemic trends and severe data limitations in AIDS case reporting impose challenges beyond any model capability.
The performance of Prophet model for HIV reactive cases aligns with studies that have already shown capability of machine learning models to capture nonlinear patterns in infectious disease data more effectively other than classical linear models. A study conducted in China(Li & Li, 2020), Brazil (Seabra et al., 2022), and sub-Saharan Africa(Aboagye-Sarfo et al., 2010) has demonstrated that HIV incidence data commonly exhibit irregular fluctuations due to diagnostic scale-ups or could be due to changes in surveillance systems.
Classical ARIMA models based on assumptions of linearity and stationarity often fail to account for such abrupt changes. Whereas, Prophet model has an additive and decomposable architecture that accommodates trend shifts, seasonal fluctuations, missing values, or irregular periodic behavior observed in HIV surveillance datasets.(Xu et al., 2020) Prophet model can trend inflections, accommodate missing data, and incorporate irregular seasonal effects (e.g. sporadic testing surges or holidays). This feature is particularly relevant for HIV data, where testing and reporting vary with campaigns or socio-cultural events. Prophet has outperformed ARIMA in other infectious disease forecasts (e.g. hand-foot-and-mouth disease) by modeling multiple seasonal patterns simultaneously (Long et al., 2023).
Similarly, performance of ARIMA model in this study was consistent with earlier findings where ARIMA provides reasonably correct forecasts of the diseases with strong seasonal or autocorrelation structure but performs fair with rapidly shifting epidemic trajectories. (Yu et al., 2014) Studies applying ARIMA to HIV incidence in China, India, and Nigeria have reported moderate error rates as that of observed for Punjab that supports the conclusion that ARIMA remains useful but limited for diseases influenced by non-stationary social and behavioral determinants.
While, deep learning models like LSTM networks are usually effective when capturing long range dependencies and complex patterns in time series. Prophet model is chosen for this study due to flexibility of handling irregularities of data such as missing values, seasonality. Prophet semi-parametric approach allows for easy incorporation of non-linear trends and seasonal variations especially in infectious disease forecasting where trends may exhibit sudden changes. Additionally, LSTM models require large datasets unlike, Punjab where data is limited and irregular.

Interpretation of Findings for HIV/AIDS cases
The Prophet model demonstrated significantly lower RMSE, MAE, and MAPE indicates more reliable short-term projections.
From January 2020 to October 2025, approximately 64,455 HIV cases have already been detected in Punjab through screening. Forecasting models predict an additional 8,490 new cases in 2026 alone, pushing the cumulative burden beyond 72,000 cases—signaling an alarming and another expanding epidemic alongside other diseases in Punjab posing another threat in country.

Nonlinear transmission behavior of HIV in Punjab is shaped by complex interactions between injecting drug use, migration, poverty, and health-seeking patterns. Such dynamics create irregular temporal patterns that Prophet captures better than ARIMA (Huang et al., n.d.).
Diagnostic variability of Prophet model is high since Punjab frequently conducts targeted screening campaigns among high-risk populations leading to sudden spikes in reactive cases that ARIMA cannot model well due to its reliance on stable autocorrelation structure. Sometimes screening among prisoners or outbreak regions and there has also been seasonal but irregular reporting cycles of HIV testing and reporting may fluctuate seasonally, decreased reporting during Ramadan, increased screening in winter, but not in a purely sinusoidal pattern. Prophet's flexible seasonality modelling accounts for this complexity.(HPHR & 2021, n.d.)
From January 2020 to October 2025, a cumulative total of approximately 34,221 AIDS cases have been documented in Punjab, reflecting late-stage disease progression. Forecasting estimates predict an additional 25,596 AIDS cases in 2026, with uncertainty bounds extending up to 46,146 cases. This projected surge raises serious concern, indicating worsening delayed diagnosis and treatment gaps and signaling the emergence of a severe public health threat alongside other growing epidemics in the province. As of the forecasting, it projects an upward sustained trajectory with number of cases to continue in 2027. Data suggest a persistent growing burden that healthcare systems will need to address promptly.
A striking finding is the substantial forecast error for AIDS cases across all models with Prophet showing particularly high MAPE and wide uncertainty intervals. Several explanations support this observation like small and irregular dataset of AIDS diagnoses represent a smaller proportion of total HIV cases that makes the time series shorter and at times harder to model(Besong et al., 2025).
Many individuals in Pakistan present for care at advanced stages that results in abrupt jumps rather than smooth case progression(Abdullah et al., 2021b). ART decentralization changes in treatment eligibility criteria and expansions in CD4 testing availability can radically alter monthly AIDS reporting trends. The high projected AIDS burden reflects delayed in the diagnosis and late entry into care of HIV due to stigmatization (Khan et al., n.d.), resulting in more individuals progressing to advanced disease stages before treatment initiation. Limited CD4 testing access is also important factor(Koirala et al., 2017), inconsistent follow-up, and gaps in early screening further contribute to the disproportionate rise in forecasted AIDS cases compared to HIV reactive cases.
AIDS case may be underreported and in Pakistan is affected by incomplete CD4 testing delays in care seeking and inconsistent follow-up, which reduce data reliability and forecasting accuracy. (Shaik et al., 2025) The finding that ARIMA $(0,1,0)\times(0,1,1)_{12}$ outperformed Prophet for AIDS cases but has high error tells that for datasets with limited nonlinearity but high noise, simpler models may fare marginally better. However, the high errors across models highlight the need for enhanced surveillance and larger, more stable datasets to improve forecasting of advanced HIV disease.
The use of sMAPE as an alternative metric provides a reliable and stable measure of forecasting accuracy in AIDS context where there is sparse in reporting and zero counts are prevalent. The sMAPE values obtained for both Prophet and Arima model tell the importance of stable metric for low incidence and fluctuating data sets. The sMAPE value 28.3% for Prophet compared with 47.6% for ARIMA model concludes Prophet flexibility in modeling non-linear seasonality and irregular reporting patterns, better handles AIDS forecasting.
Correcting negative lower bounds ensures that the confidence intervals is statistically valid. By applying the zero-floor correction to forecasts such as September 2026, we avoided predictions that suggest negative incidences.

Public Health Implications

The forecasting findings have direct implications for the HIV program in Punjab. More accurate short term projections for HIV and AIDS cases will enable Punjab AIDS Control Program (PACP) to estimate testing demand and also plan procurement of diagnostic kits. Since, HIV and AIDS are strongly influenced by targeted screening, improved forecasting can guide high concentrations upcoming cases. The poor predictability of HIV and AIDS highlight an urgent need for earlier diagnosis. A large proportion of individuals in Punjab present for care with the advanced HIV disease, which reflect the delay testing in primary healthcare settings. Strengthening routine HIV testing in general OPDs, integrating HIV screening with TB programs and decentralizing CD4 count regular testing would improve both surveillance quality and patient outcomes. Accurate forecasting also supports national progress toward the UNAIDS 95-95-95 targets by informing resource distribution for testing.

Conclusion

This study highlight emerging endemic and urgent public health concern, with forecasts indicating that HIV and AIDS in Punjab are on track to transition toward a sustained endemic pattern in the coming years. Although the Prophet model demonstrated stronger predictive performance than ARIMA for HIV case trends, both modelling approaches revealed substantial instability and uncertainty in AIDS projections, reflecting delayed diagnosis, inconsistent CD4 monitoring, and fragmented reporting systems. Model reliability is validated ensuring forecasted trends, therefore, Prophets' ability to handle missing data, flexibility in modeling seasonality and trends shift make this practical tool for public health decision makers. These patterns underscore critical gaps in surveillance, care engagement, and timely treatment initiation. Without rapid scaling up of early testing, linkage to care, and continuity of treatment aligned with the UNAIDS 95-95-95 targets, Pakistan risks facing an expanding HIV/AIDS crisis with profound clinical, social, and health-system consequences.

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