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Forecasting Crime Rates Using Time Series Models: A Comparative Analysis of ARIMAX, Prophet, and BSTS

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ABSTRACT

Crime forecasting is vital for ensuring public safety, informing policy decisions, and using resources effectively. This study compares three time series models: ARIMAX, Facebook Prophet, and Bayesian Structural Time Series (BSTS) to forecast crime rates in India using annual data from 1981 to 2022. Crime occurrence is used as an exogenous variable to assess its effect on the predictive ability. It is observed that BSTS is the best model, as it provides minimal forecast errors (Mean Absolute Error (MAE) = 8.31, Root Mean Square Error (RMSE) = 9.85), while exhibiting better explanatory power (R^2 = 0.8739) than ARIMAX and Prophet. The three models exhibit overpredictions for sudden change scenarios, thus revealing the inability of classical time series methods in dealing with structural changes. The inclusion of the exogenous variable enhances the accuracy of the predictions, though, at the risk of introducing a bias because of the strong correlation between them. The BSTS method reveals an increasing trend for crime rates and wider prediction intervals, signifying increased uncertainty for future forecasts.

1. INTRODUCTION

Crime prediction has become an increasingly important topic in view of its major impacts on security, policy, and allocation of limited resources. The ability to forecast crime enables timely response to emerging threats, plan ahead, and introduce preventive measures. The increasing volume of historical crime information has resulted in the popular use of time-series modeling as a means of investigating the problem [1].

The most popular approaches to forecasting have been based on classical statistical methods, including the Autoregressive Integrated Moving Average model and its various extensions [2]. For example, the ARIMAX approach employs external variables as a way to improve the forecast accuracy [3]. However, this forecasting method involves a set of assumptions about linearity and is unable to handle irregular data.

Some more complex methods like Facebook Prophet and Bayesian Structural Time Series (BSTS) have been developed to overcome these drawbacks. The former models the trend component through a piecewise approach [4], whereas the latter takes a Bayesian approach to modeling the trend component and uses latent variables and uncertainty to capture the underlying dynamics [5]. However, there is limited research comparing these models in the context of crime forecasting.

Another problem associated with the forecasting of crime rates is the inclusion of exogenous variables. For example, exogenous variables like crime incidence may lead to an improvement in the predictive performance. But the high correlation between such variables and the dependent variable creates an interpretational issue, which has not been adequately addressed by previous studies [6].

With the above literature review as motivation, this paper aims to perform a comparative analysis of ARIMAX, Prophet, and BSTS models to forecast crime rates based on annual data from India.

The following are the main contributions of the current paper:

- Comparative assessment of ARIMAX, Prophet, and BSTS models within a common framework
- Combination and critical examination of an exogenous variable (crime incidence)
- Incorporation of uncertainty analysis through the BSTS approach
- Validation using statistical tests to measure performance differences

2. LITERATURE REVIEW

2.1 Statistical time series approaches

Crime forecasting has traditionally been performed with statistical time series models, which are appealing due to their interpretability and rigorously developed theoretical framework [2]. Time series models such as ARIMA (Auto Regressive Integrated Moving Average) and their extensions are a common choice for modeling crime trends. The ARIMAX model extends on the ARIMA model by including exogenous variables [3].

The results of other studies indicate that ARIMA models are a good linear approximation of major changes in crime rate analysis, if the environment is relatively stable [7]. For instance, Utomo used the ARIMAX model on data of crime-related variables and found that external information actually increases predictive accuracy in the short-term [3]. However, ARIMA models hinge on linearity assumptions and stationarity which prevents them from adapting to non-linear changes and structural breaks in the data.

Furthermore, ARIMAX models are also governed by the specification of the model: coefficient estimate and order selection, for example. Differencing or order misspecification can have tremendous impact on the prediction outcome, further emphasizing model tuning [8].

ARIMAX models are also sensitive to model specification and choice of parameters. Any incorrect differencing or order choice can have a strongly negative effect on the model's ability to accurately forecast.

2.2 Machine learning and data-driven approaches

In recent years, due to the rise of machine learning and deep learning algorithms, more sophisticated techniques for crime prediction have been proposed. Machine learning algorithms such as Random Forests, Support Vector Machines and neural networks have been used to model dependencies in crime data.

A key advantage of these models lies in their ability to capture non-linear patterns and complex interactions among multiple variables [9, 10]. Such approaches can significantly outperform traditional statistical models when applied to large datasets containing many correlated features.

Nevertheless, machine learning models also have some disadvantages: they usually need a large amount of high-dimensional data, they lack interpretability and they do not explicitly incorporate the temporal structure or the uncertainty. Therefore, they may not be appropriate for aggregated or low dimensional data (e.g. annual crime data) [11].

In recent years, the use of deep learning architectures, such as recurrent neural networks and transformer-based models, for time series prediction has led to further enhancements in prediction accuracy [12, 13], even across domains.

2.3 Modern forecasting models: Prophet and Bayesian Structural Time Series

In response to the shortcomings of classical statistical and machine learning approaches, newer approaches to forecasting have emerged that are flexible and at the same time interpretable.

Researches [9, 10] show that these models are capable of modeling non-linearity and the interactions between multiple independent variables. In these cases, learning algorithms can outperform more traditional statistical modeling techniques.

Facebook Prophet is a relatively new model that predicts time series data with changes in trend and seasonal variations [14]. It assumes that the changes in the trend can be described in a piecewise linear/logistic growth model. Its application to crime forecasting was based on the fact that it can automatically detect change points, handle gaps in the dataset and non-linear trends. However, predefined trend structures may hinder the ability to catch anomalous sudden irregular fluctuations.

BSTS offers a probabilistic approach to modeling the time series by examining them as a sum of unobservable components such as overall trend and regression components [5]. A major benefit to using BSTS is the fact that uncertainty is explicitly built into the forecasting through the posterior distribution, and can be ideal if unobservable factors are contributing to the data [15].

BSTS has been shown to handle well classes of non-stationary and irregular behavior by allowing components of models to change over time rather than relying on assumption of constant relationships [16, 17].

2.4 Research gap and study motivation

There are still several existing gaps in the literature of crime rate forecast, even though a wide variety of forecast methods has been adopted in the current research.

Firstly, several studies are directed toward either statistical models or machine learning algorithms, and comparisons of these models lack a common experimental basis, therefore difficult to evaluate the characteristics of various kinds of models [18].

Secondly the use of exogenous variables in crime forecasting is not clearly addressed. Although exogenous variables can enhance the prediction precision, the high correlation between the exogenous variables and the response variable increases the concern on over specificity and explanatory power. Limited research is available in this area [19].

Third, uncertainty estimation is often ignored in the literature on crime forecasting. The majority of prediction models only produce a single prediction, not an estimate of the uncertainty associated with the prediction [20, 21].

Given these shortcomings, the current paper compares the ARIMAX, Prophet, and BSTS models in a systematic fashion for a unified dataset and evaluation procedure. It also discusses the influence of an external regressor and underscore the importance of uncertainty in enriching forecast interpretation.

3. METHODOLOGY

3.1 Data description and preprocessing

This paper uses annual crime data for India from 1981 to 2022. Two variables have been considered:

- Crime Rate: total crime per 100,000 population (target variable)
- Crime Incidence: total number of reported crime cases (exogenous variable)

The dataset was first scrutinized to check for missing values and inconsistencies; no missing observations were found. Also, the crime incidence variable was scaled prior to the comparison of the models for comparability by the Min–Max scaling method. This was done in order to maintain comparable scales of the exogenous input, hence to stabilize the magnitude and avoid undue influence on the estimation.

The Pearson correlation coefficient between crime rate and crime incidence yielded a strong positive correlation (r = 0.8921), indicating possible multicollinearity, which could impact the stability and interpretability of regression-based models.

The data was divided into:

- Training set: 1981–2017
- Test set: 2018–2022

This split maintains temporal ordering so it can be used for out-of-sample evaluation.

3.2 Stationarity and transformation

ARIMAX takes stationary input, the crime rate series was therefore subjected to the Augmented Dickey Fuller (ADF) test [17]. The test shows the series is not stationary, then order of difference is chosen two (d = 2), thus making the series stationary.

The exogenous variable (crime incidence) was used in scaled form without optional differencing since it was included as a regressor rather than as an independent process.

3.3 Model specifications

3.3.1 ARIMAX model

The ARIMAX model was implemented using the SARIMAX framework [2]. The order of the models was determined through an exhaustive grid search over various combinations of autoregressive (p), differencing (d), and moving average (q) parameters with Akaike Information Criterion as the search metric [20].

The optimal model was identified as: ARIMAX (0, 2, 2)

Crime Incidence (scaled) was used as an exogenous regressor. This approach ensures:

- systematic parameter selection
- reproducibility
- avoidance of arbitrary mode specification

3.3.2 Prophet model

The implementation of the Prophet model was based on the standard additive set-up with a piecewise linear trend [4]. The model was further generalized by inserting the scaled crime incidence variable as an external regressor.

The model configuration includes:

- Automatic trend detection
- Change point handling
- Inclusion of exogenous input

A baseline configuration was chosen to enable a fair comparison among models and to prevent overfitting, due to the small size of the data set.

3.3.3 Bayesian Structural Time Series

The BSTS model was implemented using a state-space formulation [16] with the following components:

- Local linear trend component in order to accommodate slow changes
- Regression component incorporating crime incidence
- Utilize the Bayesian inference framework to fit the posterior distributions

Compared to the deterministic models BSTS expresses the observed series as a combination of latent states that change over time. One of BSTS advantages is its ability to trace hidden effects of the hidden states. We extracted forecasts based on the posterior predictive distributions, so that meaningfully derived intervals for uncertainties [15]. Based on the posterior predictive distributions, we were able to generate forecasts and derive uncertainty intervals.

3.4 Model evaluation

Model performance was evaluated using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)

These metrics offer complementary views of the predictions: how accurate they are, how large the errors are, and how much variance they explain [20].

3.5 Validation strategy

To assess model robustness, two validation approaches were employed:

- Train–test evaluation over 2018–2022 test period
- For walk-forward validation where models were iteratively re-estimated and re-evaluated one-step-ahead forecasts

Hence, it will not only make the results less dependent on the way the data is split, but also give a more reliable estimate of the performance of the model.

3.6 Statistical comparison

In order to assess if the differences in model performance were statistically significant, we performed a paired t-test of the absolute forecast errors of BSTS and ARIMAX.

This test evaluates whether the observed difference in prediction errors is statistically likely to be due to chance or whether it is a true performance difference.

3.7 Forecasting procedure

The trained models were then used to forecast 2023–2027, which was after the model evaluation.

For models that necessitate outside inputs, future values of crime incidence were estimated with a linear trend based on the last-year values. This introduces some uncertainty, but permits comparison by standardizing on the same measure.

BSTS predictions also generate uncertainty bands, providing a probabilistic range of the future outcomes rather than a point estimate [15].

4. RESULTS

4.1 Quantitative performance evaluation

The forecast accuracy of the ARIMAX, Prophet and BSTS models was assessed by the statistical measures of MAE, RMSE and R^2, as summarized in Table 1 [22-24].

From Table 1, all the evaluation measures demonstrate that the BSTS model performs best with the smallest predictive errors and the greatest explanatory power, Prophet performs the second best by lowering MAE and RMSE and ARIMAX performs the least.

It is also noteworthy that the sequence of the models is stable across the three measurements. Hence the differences are not dependent on the assessment criterion but rather give the pattern of the prediction ability of the models. Although the improvement is moderate, it is consistent and therefore significant.

Table 1. Performance comparison of forecasting models

Model	MAE	RMSE	R²
ARIMAX	9.91	11.75	0.8205
Prophet	8.68	10.26	0.8631
BSTS	8.31	9.85	0.8739

Note: Bayesian Structural Time Series (BSTS); Mean Absolute Error (MAE); Root Mean Square Error (RMSE)

4.2 Forecast comparison

Figure 1 displays the predicted and observed values for the test period. All three models reflect the upward trend that appears in the series, including the sharp rise in 2020, and appear to follow the series consistently.

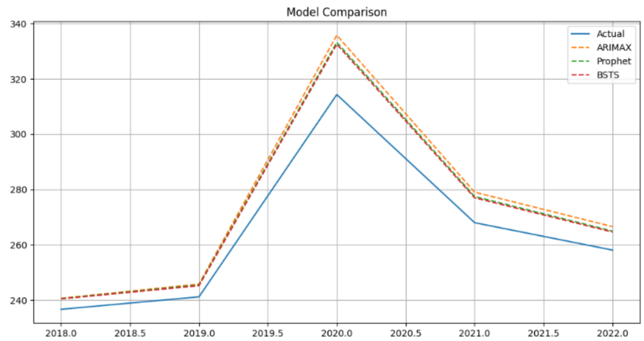

Figure 1. Model forecast compared to the test period (2018–2022)

In particular, across all models there is an overprediction of the magnitude of the 2020 peak, as well as a sustained lifting of predictions above the observations in subsequent years. The results indicate that the forecasted values from the various models are relatively closer to the actual values in the test period. Out of all the models, BSTS has lower deviations from the actual series, ARIMAX has highest deviations from the actual series (in peak year of series) and Prophet shows intermediate deviations from actual series.

4.3 ARIMAX model results

The ARIMAX model as shown in Figure 2, captures the overall trend in the series but gives a considerably larger value to the peak in 2020. This indicates that the model is overly sensitive to recent changes in the time series and the exogenous variable.

The residual plot as shown in Figure 3 exposes a distinct systematic trend of mostly negative residuals spanning the testing period, indicating systematic bias rather than random error. The residuals are most severe in 2020, signifying limited ability of the model to adapt quickly when there is a sudden structural break.

The fact that this bias persists indicates that the ARIMAX specification does not fully describe the dynamics present during periods of accelerating change and thus exhibits a persistent deviation from observed values.

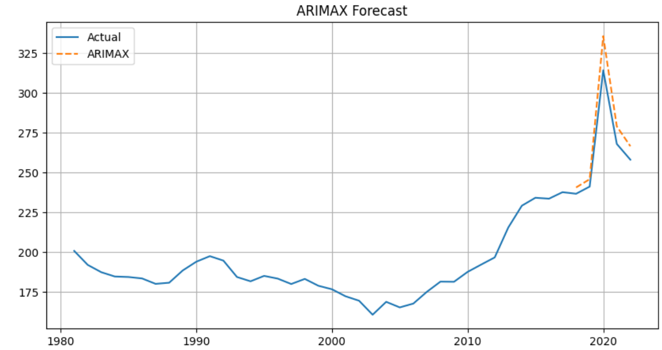

Figure 2. Predicted versus actual values from the ARIMAX model

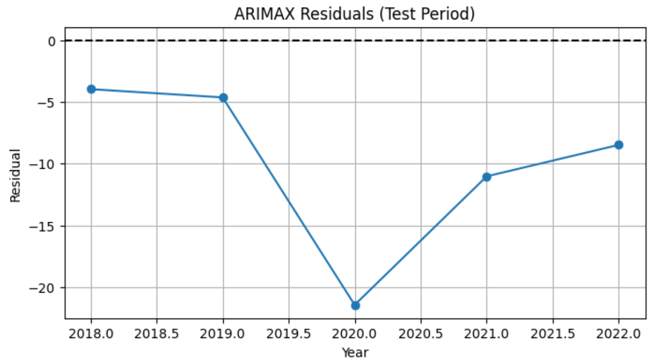

Figure 3. Residuals of ARIMAX model for the test period

4.4 Prophet model results

As shown in Figure 4, the Prophet model is able to fit the underlying trends more smoothly than ARIMAX and generates forecasts which are more consistent with the observed values after the 'peak'. However, it also overestimates the peak value in 2020 just like ARIMAX did, showing that the model depends too heavily on trend extrapolation.

Despite the smaller magnitude of deviation relative to ARIMAX, the persistent trend of overprediction indicates that Prophet model too assumes trend persistency in the data and does not adequately account for structural breaks.

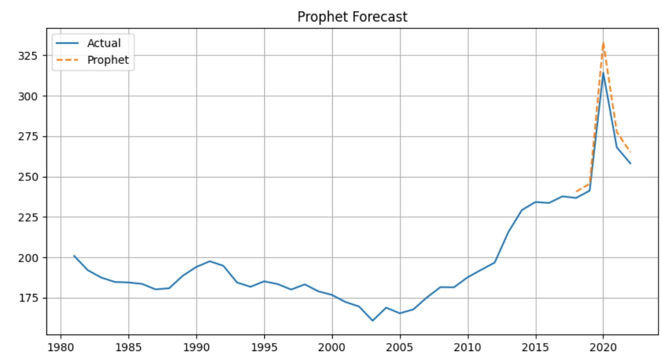

Figure 4. Prophet forecast versus actual values

4.5 Bayesian Structural Time Series model results

The forecasts generated by the BSTS model, shown in Figure 5 are consistently closer to the observed values for the entire test period. Additionally, the BSTS model allows for the uncertainty in the model to be estimated with the use of prediction intervals (posterior credible intervals).

The expansion of these time intervals at peak is consistent with higher variance at the sudden transitions in the data, suggesting that our model does not squeeze to one path excessively. This flexibility in modeling fluctuations improves robustness and predictive reliability.

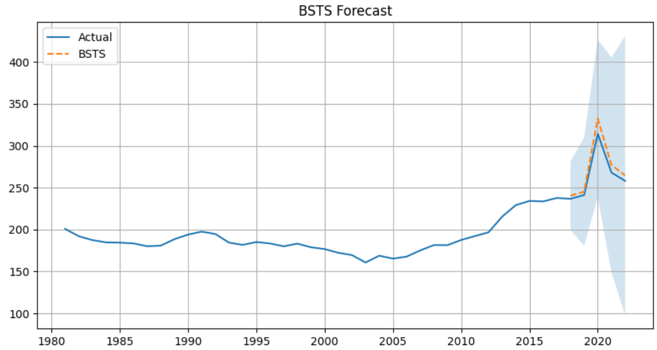

Figure 5. Bayesian Structural Time Series (BSTS) forecast with uncertainty intervals

4.6 Visualization of performance metrics

The heatmap as shown in Figure 6, offers a condensed view of model evaluation performances across all metrics. It shows with comparison that in terms of lower errors values and higher R^2, BSTS out-performs while Prophet and ARIMAX follow in decreasing order of the performance.

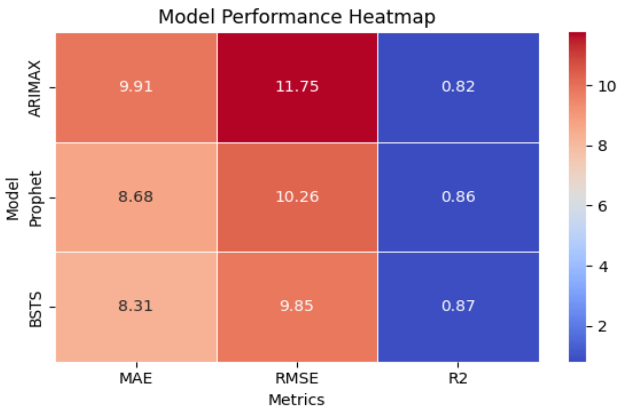

Figure 6. Performance metrics heatmap

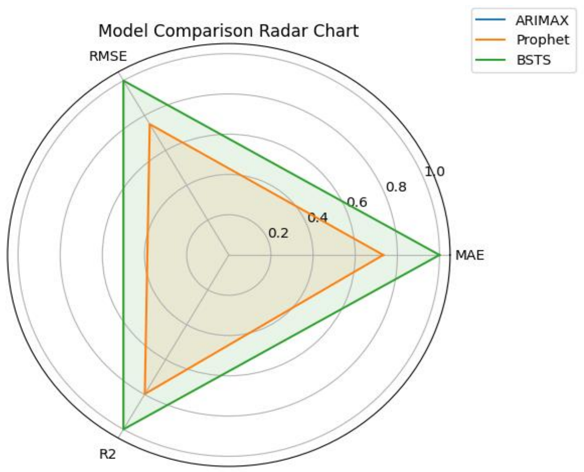

Figure 7. Radar chart of normalized performance indicators

The radar chart as shown in Figure 7, also makes similarities between models more apparent by normalizing the evaluation criteria. It can be seen that BSTS outperforms the other approaches in every aspect, giving it the greatest coverage.

4.7 Robustness and statistical testing

For walk-forward validation, the RMSE of ARIMAX was 7.77, which was less than the RMSE from static test set (11.75). This suggests that the model has fairly good generalization ability and does not perform poorly due to a single train–test split.

In order to test whether the performance gain observed is statistically significant, a paired t-test of the absolute errors between the BSTS and ARIMAX models was performed. The output is:

- T-statistic = -2.9154
- P-value = 0.0434

The p-value shows that this result is statistically significant at the 5% significance level, which means that the better performance of BSTS compared with ARIMAX would not be due to randomness. Nevertheless, it should be taken with care considering the test sample is quite small.

4.8 Future forecast interpretation

The BSTS model's forecast as shown in Table 2, suggests a somewhat steady increase in crime rates during 2023–2027, with forecasted values in the range of 255.96 to 287.97. The prediction intervals, on the other hand, becomes quite broad as the time horizon extends.

Table 2. Forecasted crime rate using Bayesian Structural Time Series (BSTS) (2023–2027)

Year	Forecasted Crime Rate	Lower Bound	Upper Bound
2023	255.96	215.10	296.81
2024	263.96	199.45	328.47
2025	271.97	177.84	366.09
2026	279.97	151.69	408.25
2027	287.97	121.71	454.24

The lower and upper bounds deviate significantly from each other after 2024, implying future crime rates are uncertain even with the general trend being upward. This reflects the model's sensitivity to possible structural breaks or external shocks that cannot be fully captured using historical data alone.

5. DISCUSSION

5.1 Interpretation of comparative performance

The analysis has shown that on all the metrics, the forecast based on BSTS is better than ARIMAX and Prophet. This indicates structural differences between the models.

There is a fundamental difference in the way the models capture the underlying data dynamics. While ARIMAX and Prophet treat the trend as an explicit, deterministic extrapolative variable, BSTS models latent state processes explicitly, allowing their evolution. This adaptation makes BSTS more robust to smooth changes and anomalies in the trend, producing more stable predictions.

5.2 Systematic overprediction and structural effects

All models show an inherent bias towards the over-prediction of the peak observed in 2020 followed by an elevated forecast. This is suggestive of the models' treatment of the sudden rise as a trend continuation and not a structural change. This reflects a fundamental limitation of time-series forecasting models due to their assumption of temporal continuity and pattern extrapolation.

However, there is significant variation in the extent of this bias among the three models. The bias for ARIMAX is the highest because of its dependence on differenced trends and exogenous variable. On the other hand, Prophet reduces this tendency through its piecewise trend modeling. However, it is unable to deal with structural changes due to the persistence assumption in trend dynamics. BSTS exhibits the lowest bias among the models.

5.3 Effect of the exogenous variable

The addition of the crime incidence as an exogenous variable improves predictive performance but introduces a bias in the predictions due to strong correlation with the target variable. This leads to a trade-off between interpretability and predictive performance. It does improve the capability of short-term forecasts, but it may capture the same information as the target variable, which prevents the model from understanding the effects of structural transformations.

5.4 Role of uncertainty in forecasting

A unique trait of BSTS is its quantification of uncertainty through the prediction intervals (posterior credible intervals). As the window to the peak expands, the prediction intervals (posterior credible intervals) expand reflecting the increasing uncertainty in association with sudden jump.

This characteristic is particularly essential in practical applications. Point forecasts might give a false sense of precision while an estimate of uncertainty shows a more realistic spread of possible results. So, in this case the fact that the BSTS model gives more accurate forecasts and also explains more clearly the levels of uncertainty around those forecasts is a significant advantage.

5.5 Robustness and statistical significance

The walk-forward validation results indicate good generalization ability of ARIMAX and support that its results are not solely a coincidence of a certain train–test split. Nevertheless, the advantage of BSTS is still transparent.

The statistical test provides additional evidence for the above, suggesting that the performance of the two is statistically significant at the 5% significance level. But, the small size of the test sample prevents this conclusion from being very strong, and should therefore be interpreted as supportive rather than definitive evidence.

5.6 Limitations and implications

There are various limitations that must be considered while analyzing the outcomes of this study. Firstly, annual data does not provide temporal granularity and thereby making it difficult for the model to identify short-term variations in the data. Moreover, the limited size of the sample may limit the statistical inference in this regard. Another potential issue is that the strong correlation between the target and exogenous variables might render some of the results irrelevant.

However, the results indicate that methods dealing with structural uncertainty and capable of adjusting to changing patterns, such as BSTS, are preferable in situations involving time series with irregular trends.

6. CONCLUSIONS

This paper compares the ARIMAX, Prophet, and BSTS models for predicting crime rates in India from annual data. A common metric-based framework was used to evaluate these models quantitatively and visually.

The findings show that the BSTS model demonstrates the highest predictive accuracy in terms of the lowest errors and best explanation capabilities. The performance advantage of this model is attributable to its ability to learn the latent structure and incorporate uncertainty, thereby accounting for alterations in the data more efficiently. On the contrary, ARIMAX and Prophet models rely on trend extrapolation resulting in systematic overestimation in case of sharp deviations.

One of the major findings of this analysis is that all three models exhibit overestimation of the number of crimes in 2020 which shows the limitations of time-series forecasting techniques in case of structural shifts. As expected, crime incidence as the exogenous variable contributes greatly to the forecast accuracy; however, the relationship may introduce bias.

In practical applications, models with structural flexibility and uncertainty, like BSTS, are appropriate for making data-based decisions in preventing crime and allocating resources.

This study has certain limitations due to its aggregated annual data, relatively short forecast horizon, and redundancy in the exogenous variable. Further research can expand on the current one by considering higher frequency data and various exogenous variables.

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