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Comparing Facebook Prophet and ARIMA for Forecasting Online Gambling Transactions in Indonesian E-Wallets

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ABSTRACT
The rapid expansion of digital financial services in Indonesia has driven widespread adoption of e-wallet platforms, while also enabling the growth of illegal online gambling activities. This study presents a predictive framework for detecting gambling-related behavior on Indonesian e-wallet platforms using the Facebook Prophet time series forecasting model, with ARIMA employed as a comparative benchmark. By analyzing historical transaction data flagged as suspicious or potentially linked to gambling, both models are used to capture seasonal trends and detect anomalies that signal future high-risk activity. The results show that Prophet effectively anticipates spikes in gambling-related transactions, often outperforming ARIMA in capturing complex seasonal patterns. These findings highlight the potential of time series forecasting to enhance fraud detection systems by enabling proactive interventions during predicted high-risk periods. This research contributes to the field of financial fraud prevention by demonstrating the value of integrating predictive analytics particularly Prophet into efforts to combat illicit behavior within Indonesia's evolving digital finance ecosystem.

Keywords: Online Gambling, E-Wallet, Fraud Detection, Time Series Forecasting, Facebook Prophet.

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1. INTRODUCTION

Indonesia's rapid digital transformation in financial services has significantly advanced financial inclusion, particularly through the widespread adoption of e-wallet platforms. These platforms have enabled millions of Indonesians including those in remote and underserved areas to access digital financial services, narrowing the financial access gap (Husainah et al., 2023). However, this technological progress has simultaneously created opportunities for illicit activities. Most notably, illegal online gambling has emerged as a pressing phenomenon at the intersection of digital finance, regulatory enforcement, and public welfare.

Although online gambling is explicitly prohibited under Indonesian law, including the revised Undang-Undang Informasi dan Transaksi Elektronik (UU ITE, 2024), its digital manifestation continues to expand rapidly. Exploiting the anonymity and decentralization of online financial platforms, gambling operators utilize disguised merchant codes, anonymous top-ups, and peer-to-peer transactions to evade detection (Komdigi, 2024). The Indonesian government, through entities such as the Ministry of Communication and Information (Kominfo) and the Financial Transaction Reports and Analysis Center (PPATK), has responded by blocking over 2.1 million gambling-related websites and reinforcing regulatory frameworks via Presidential Decree No. 21 of 2024 and further amendments to the UU ITE (PPATK, 2025; Komdigi, 2024). Nevertheless, online gambling transactions are estimated to have reached Rp600 trillion by mid-2024, with a growing number of participants including minors and other vulnerable groups (PPATK, 2025).

The scale and sophistication of this phenomenon have exposed the limitations of traditional monitoring and audit mechanisms. Rule-based transaction filters and manual reviews are increasingly inadequate in addressing the rapidly evolving and concealed nature of digital gambling fraud. This has prompted a growing emphasis on data-driven approaches, with organizations leveraging analytics reporting significantly faster response times and greater accuracy in identifying irregular patterns (Association of Certified Fraud Examiners, 2024; Sidauruk, 2024). These developments reflect a broader institutional shift toward proactive, analytics-based oversight.

The urgency for predictive systems is underscored by the complex temporal dynamics unique to online gambling transactions. These behaviors are influenced by nonlinear patterns, recurring spikes around paydays and holidays, and sudden surges triggered by major events such as sports tournaments (Husainah et al., 2023). Reactive approaches are insufficient to handle such volatility, making predictive models capable of forecasting high-risk periods essential for preemptive regulatory intervention and resource allocation.

This study compares the performance of two time series forecasting models AutoRegressive Integrated Moving Average (ARIMA) and Facebook Prophet in anticipating spikes in illicit online gambling activity in Indonesia. The goal is to evaluate which model is more effective in terms of accuracy, scalability, and interpretability for use in financial crime surveillance systems.

Despite the growing body of research on machine learning and time series forecasting for financial fraud detection, a significant research gap remains: few empirical studies have applied predictive forecasting models specifically to online gambling transactions within Indonesian e-wallet platforms. Furthermore, existing comparative studies between forecasting methods have largely focused on general financial or retail contexts, leaving the unique behavioral characteristics of online gambling such as event-driven surges, holiday effects, and weekend seasonality largely unexplored in the academic literature. This study addresses that gap by comparing ARIMA and Facebook Prophet, two interpretable time series models that balance forecasting accuracy with the

transparency required in regulatory and institutional settings (Taylor & Letham, 2018; Kontopoulou et al., 2023). A detailed discussion of each model's characteristics and prior applications is provided in the Literature Review.

Ultimately, this study contributes to Indonesia's broader digital economy protection strategy by supporting the development of scalable, explainable, and anticipatory fraud detection tools. By identifying peak periods of illicit online gambling activity in advance, financial regulators, law enforcement, and policy stakeholders can act decisively issuing targeted warnings, enhancing monitoring protocols, or blocking transactions before societal harm escalates.

2. LITERATURE REVIEW AND HYPOTHESIS

This study is grounded in the theoretical framework of proactive fraud detection, which posits that effective financial crime prevention requires a shift from reactive, rule-based mechanisms toward anticipatory, data-driven approaches (ACFE, 2024; Hasan, 2024). Within this framework, fraud is understood not as a static phenomenon but as a dynamic, evolving threat that exploits technological advancements faster than traditional oversight systems can respond. This overarching perspective connects the key dimensions of the present study: (1) the phenomenon of online gambling proliferating through digital payment ecosystems, (2) the inadequacy of conventional detection methods, (3) the potential of time series forecasting as a proactive tool, and (4) the comparative suitability of ARIMA and Facebook Prophet for this purpose. The following subsections review each of these dimensions in turn.

Phenomenon: Online Gambling in E-Wallet Ecosystems

The proliferation of e-wallet platforms has significantly reshaped Indonesia's financial ecosystem by increasing access to digital payments and supporting financial inclusion. However, this growth has also enabled illicit financial activities, notably online gambling, which remains strictly prohibited under Indonesian law. According to PPATK (2025), over Rp238 trillion in online gambling transactions were recorded by September 2024, with projections reaching Rp900 trillion by year-end (Indonesia Business Post, 2024). The Ministry of Communication and Digital (Kominfo) has responded by blocking more than 5.7 million pieces of online gambling content and coordinating with Bank Indonesia to freeze over 500 e-wallet accounts linked to suspicious activity. Despite such interventions, the scale and persistence of these illicit transactions reveal systemic detection challenges that demand new predictive approaches.

From Reactive to Proactive Detection: Machine Learning and Time Series Forecasting

Rule-based fraud detection systems built on static thresholds and pre-programmed rules are increasingly inadequate for detecting modern, adaptive fraud. As Hasan (2024) notes, these systems "react after fraud has occurred" and cannot autonomously evolve to capture new fraud strategies. This has led to a shift toward machine learning (ML) and statistical forecasting models, which can proactively identify anomalous behavior and evolving threats through data patterns (Hilal et al., 2022; Hasan, 2024; Thimonier et al., 2024).

ML techniques, such as decision trees, neural networks, and support vector machines, have demonstrated superior predictive capabilities compared to traditional models (Gupta, 2019; Ngai et al., 2011; Aros et al., 2024). However, their reliance on large, labeled datasets and limited interpretability has hindered practical deployment, especially in compliance-heavy sectors like finance. This has led to increased interest in time-series forecasting methods, which are more interpretable and better suited for sparse, sequential data (Dal Pozzolo et al., 2014; Jurgovsky et al., 2018). Notably, ARIMA and Facebook Prophet offer

scalable alternatives that can detect unusual transaction patterns by analyzing historical time trends and seasonality (Taylor & Letham, 2018; Kontopoulou et al., 2023).

Applying the Proactive Framework: ARIMA and Facebook Prophet in Financial Fraud Detection

The ARIMA model (Auto Regressive Integrated Moving Average) has long been used in economic forecasting and financial fraud detection for modeling linear trends and identifying statistical anomalies in transactional data (Moschini et al., 2021). While reliable, ARIMA assumes stationarity and struggles with complex seasonal effects or abrupt structural changes, which are often present in gambling-related behavior.

In contrast, Facebook Prophet is designed for business forecasting and offers greater flexibility in modeling nonlinear trends, multiple seasonalities (e.g., weekly, monthly), and holiday/event effects (Taylor & Letham, 2018). Prophet is also robust to missing data and outliers and requires minimal manual tuning, making it highly practical for operational fraud detection. Studies comparing Prophet and ARIMA show that Prophet consistently delivers lower forecasting error in seasonal behavioral datasets (Kwarteng, 2024; Yadav, 2022).

Model Selection Rationale: Balancing Accuracy, Interpretability, and Regulatory Requirements

While advanced machine learning models such as LSTM and XGBoost offer improved accuracy in some cases, they require extensive data, tuning, and computational resources, and often lack the transparency necessary for regulatory compliance (Adekoya et al., 2023; Betti & Sarens, 2020). In contrast, ARIMA provides a robust statistical baseline, while Prophet introduces interpretability with superior capacity to model seasonality and changepoints relevant to online gambling behavior.

Moreover, several researchers emphasize the importance of simplicity and interpretability in fraud detection tools used by internal auditors and financial institutions (Alfian, 2023; Islam & Stafford, 2022; Novita & Anissa, 2022). These practical considerations combined with Prophet's ability to integrate domain-specific events like holidays or major sports matches support the selection of Prophet and ARIMA as the primary models for this study.

Research Gap and Hypotheses

While prior research has examined machine learning and time series forecasting methods in financial fraud detection, there remains a lack of empirical studies applying these models specifically to online gambling activity within Indonesian e-wallet platforms. Furthermore, few studies compare Prophet and ARIMA in the context of digital financial crime under local regulatory constraints.

This study addresses this gap by applying both models to real-world e-wallet transaction data linked to verified gambling users in Indonesia. The aim is to determine which method more accurately predicts risky transaction periods and can serve as a reliable early-warning system.

H_0: There is no significant difference in forecasting performance between Facebook Prophet and ARIMA.

H_1: Facebook Prophet can effectively forecast online gambling transaction patterns within e-wallet platforms in Indonesia, enabling proactive fraud detection and prevention.

3. METHODS

Sampling

This study analyzed online gambling activity on the LinkAja e-wallet platform, specifically focusing on users who were reported by Bank Indonesia and verified by LinkAja's fraud team as online gamblers. The sample consisted of over 300 unique MSISDNs, from which user-level transactional data was aggregated into daily flagged transaction counts

spanning from January 2024 to April 2025. These users were selected due to high-risk indicators, including suspicious geolocations and behavioral patterns identified by LinkAja's internal Fraud Detection System (FDS).

Data Collection

Data was sourced from LinkAja's internal Google BigQuery data warehouse. Verified users were cross-referenced against transaction logs and fraud detection events using gambling online rules. These rules are linked to an internal database. Aggregation was performed at the daily level to build a time series of flagged user activity.

The final dataset contained:

a. ds: the transaction or rule hit date
b. y_flagged_input: count of flagged transactions for the verified MSISDNs per day

Measures

The primary variable used for modeling was y, representing the number of daily flagged transactions, modeled over time (ds). Preprocessing steps included:

a. Replacing 0 values with 1 to maintain numerical stability and avoid division by zero during evaluation.
b. Retaining only verified online gambling users to ensure high data precision.

The dataset was divided into:

a. Training set: Full data minus the last 30 days
b. Test set: Final 30 days used for model evaluation

Modeling Techniques

The study employed Facebook Prophet, a time series forecasting algorithm based on the following additive model:

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

Where:

a. g(t) is the trend function.
b. s(t) represents seasonality.
c. h(t) represents holiday effects.
d. εt is the error term.

The Prophet model was trained on the cleaned dataset, and forecasts were generated for the final 30-day test period. The model was also evaluated visually and quantitatively.

The study also employed ARIMA (Auto Regressive Integrated Moving Average), a widely used time series forecasting method defined by the equation:

$$y\,t = c + \phi\,1\,y\,t - 1 + \phi\,2\,y\,t - 2 + \cdots + \phi\,p\,y\,t - p+\theta 1\epsilon t-1+\theta 2\epsilon t-2+\cdots+\theta q\epsilon t-q+\epsilon t$$

a. y(t) is the differenced series after applying ddd order differencing to achieve stationarity.
b. c is a constant.
c. ϕ1,ϕ2,...,ϕp are autoregressive coefficients (AR part).
d. θ1,θ2,…,θq are moving average coefficients (MA part).
e. ϵt is the white noise error term at time t.

Evaluation Metrics

The performance of the model was evaluated using:

a. Mean Absolute Error (MAE):
   $MAE=n1i=1\sum n|yi-y\hat{}i|$
b. Root Mean Squared Error (RMSE):
   $RMSE=n1i=1\sum n(yi-y\hat{}i)2$

Where:

a. yi is the actual value.
b. y^i is the predicted value.
c. n is the number of forecast days (30).

The actual and predicted values were plotted for visual analysis, and performance metrics were printed to validate model accuracy.

4. RESULTS AND DISCUSSION

Descriptive Results

This forecasting plot below showed a relatively stable pattern of daily flagged activity, with seasonal fluctuations observed across weekdays and weekends. The average number of flagged transactions ranged between 4 and 8 cases per day, with periodic spikes reaching 10

or more. These spikes typically occurred during weekends, consistent with common behavioral trends in gambling-related activity. Visual inspection of the forecast output (Figure 1) shows that the Prophet model successfully captured the upward linear trend and weekly seasonality, confirming the presence of structured patterns in user behavior over time.

Components

Prophet's built-in decomposition revealed the overall trend showed a steady increase over the observation period (2024–2025). Figure 2 shows a rising trend in flagged transactions and clear weekly seasonality. Activity peaks on weekends especially Saturday and Sunday and drops midweek, suggesting online gambling is more active during leisure days.

Figure 1. **Prophet Forecast of Daily Flagged Gambling Transactions**

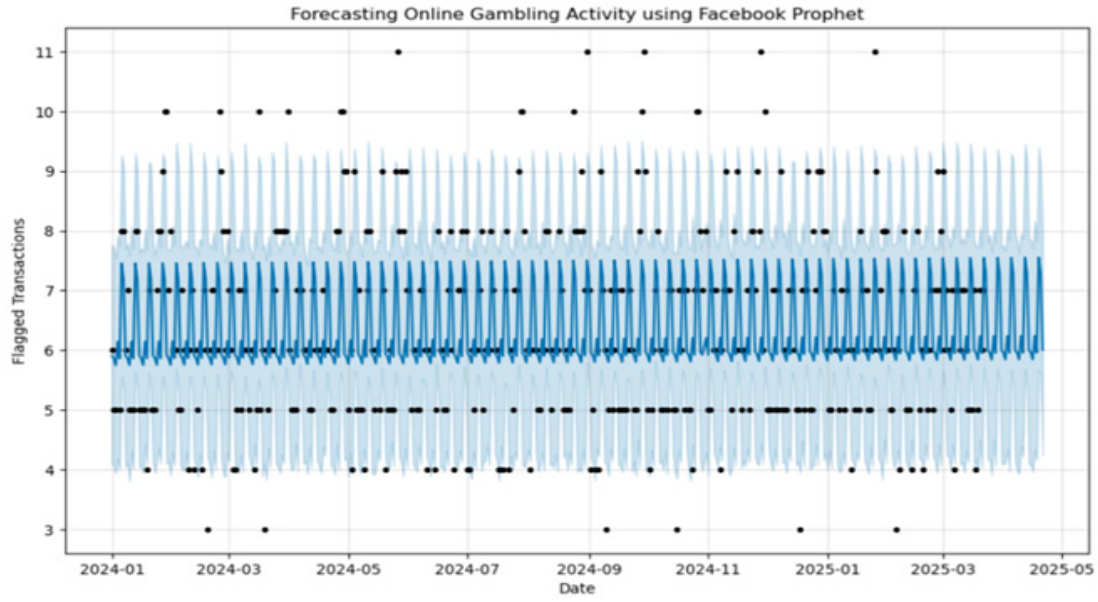
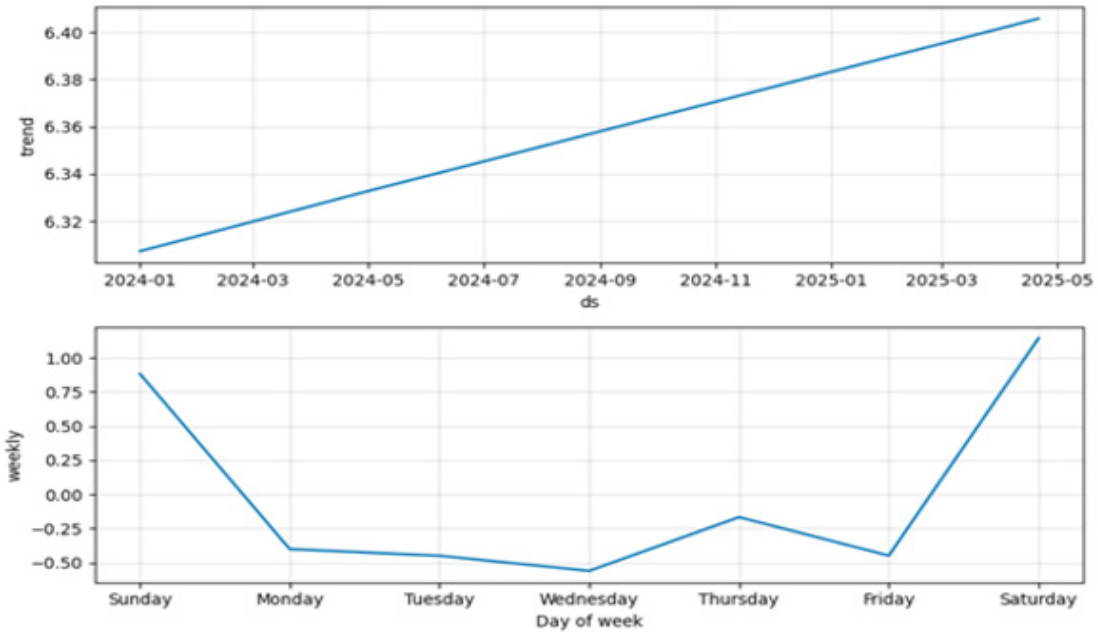


Figure 2. **Trend and Weekly Seasonality Components**



This weekend spike may also be influenced by major football leagues like the English Premier League, Serie A, and others, which typically take place every weekend. Figure 3 shows a holiday effect on flagged transactions. The top panel identifies frequent national holidays throughout the timeline, while the bottom panel reveals that the average number of flagged transactions is significantly higher on holidays than on non-holidays.

Figure 4 indicates a strong link between football events and spikes in flagged transactions. The distribution shows that flagged activity is noticeably higher on days with football matches compared to non-event days.

Forecast Accuracy

The model's performance was evaluated by comparing predicted values to actual flagged transactions over the final 30 days

Figure 3. **Holiday Seasonality**

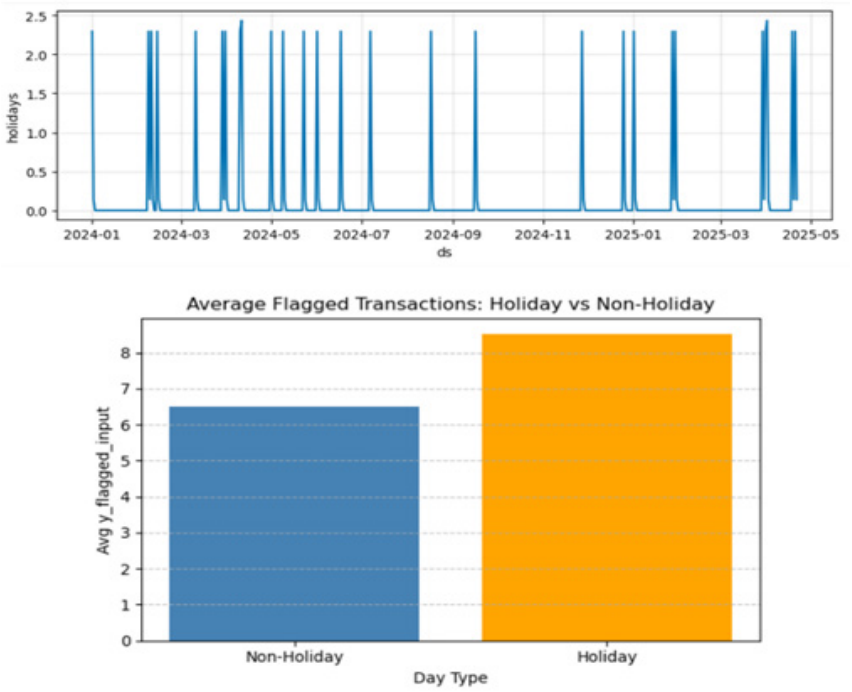
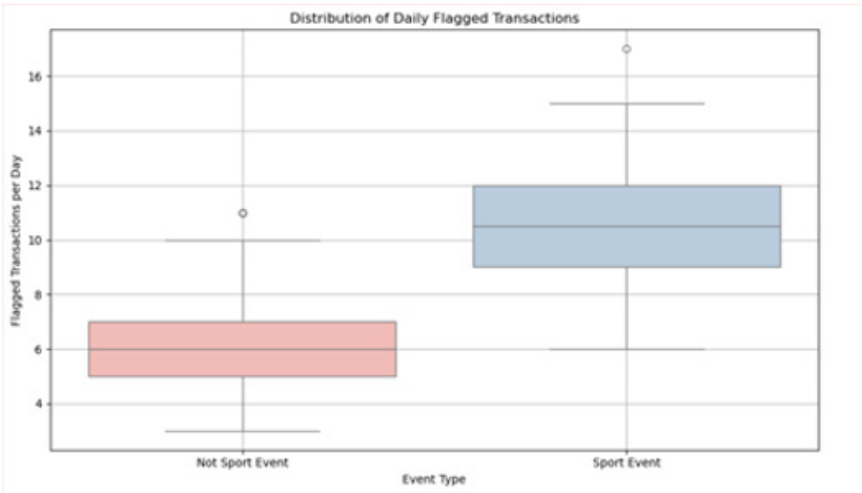


Figure 4. **Sport Event (Football) Seasonality**



in the dataset. The comparison (Figure 5) shows that Prophet's forecasts were able to follow the actual values closely with minor underestimations, especially during short-term spikes.

In contrast, ARIMA exhibited a slightly higher error rate than Prophet in both RMSE and MAE metrics (Table 1). Although ARIMA effectively captured the overall trend of flagged transactions, it struggled to adapt to sharp fluctuations and holiday-related effects. Prophet's strength lies in its ability to incorporate external regressors and multiple seasonal components, allowing it to model domain-specific patterns such as holidays and payday windows more accurately. Both models demonstrated strong forecasting performance for daily suspicious transaction volumes, as reflected by their low error values.

While these results do not fully reject the null hypothesis (H0) which states that there is no significant difference between the forecasting performances of Facebook Prophet and ARIMA the marginally better accuracy of Facebook Prophet supports the alternative hypothesis (H1). This confirms Prophet's superior ability to forecast online gambling activity for proactive fraud detection in e-wallet platforms, whereas ARIMA serves as a useful baseline but lacks the flexibility to fully capture complex behavioral signals in this domain.

Discussion

Restatement of the Study's Purpose

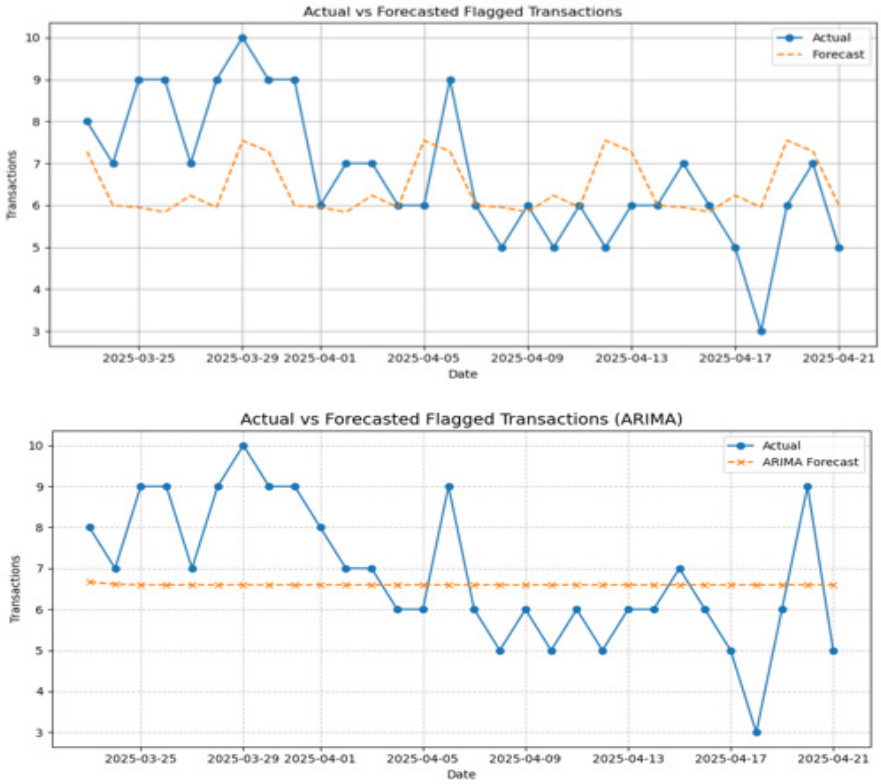
The primary objective of this study was to evaluate and compare the effectiveness of two time series forecasting models

Table 1. **The Result of Evaluation Metrics**

Model	RMSE	MAE
Facebook Prophet	1.29	1.65
ARIMA	1.40	1.69

Source: Processed Data

Figure 5. **Actual vs. Forecasted Flagged Transactions Facebook Prophet and ARIMA**



Facebook Prophet and ARIMA in predicting online gambling transaction patterns within an Indonesian e-wallet platform. By assessing their forecasting accuracy, the study aimed to determine which model better supports fraud detection teams in adopting a proactive stance, enabling them to anticipate high-risk periods for suspicious activity rather than responding reactively after fraudulent transactions occur.

Significance and Contributions of the Study

This research is significant because it addresses a critical gap in current fraud detection systems, which are often reactive and dependent on rigid rule-based mechanisms. By comparing Facebook Prophet and ARIMA, the study evaluates the strengths and limitations of two established time series forecasting models in predicting online gambling transaction patterns. The findings highlight the value of incorporating seasonality, holidays, and trend-based signals in fraud prediction models. Furthermore, this study contributes to the growing body of literature advocating for predictive analytics in financial crime prevention and is among the first in Indonesia to apply and evaluate time series forecasting methods on e-wallet transaction data specifically targeting gambling-related activities.

Summary of Results in Relation to the Hypothesis

The evaluation results revealed that both Facebook Prophet and ARIMA performed reasonably well in forecasting daily flagged transactions. Prophet slightly outperformed ARIMA, achieving lower RMSE (1.29 vs. 1.40) and MAE (1.65 vs. 1.69) scores. While these results do not fully reject the null hypothesis (H0) which posits no significant difference in forecasting performance between the two models the marginally better accuracy of Facebook Prophet supports the alternative hypothesis (H1). Prophet's ability to incorporate seasonal effects, holiday influences, and changepoints contributed to its stronger alignment with complex transaction patterns, suggesting its suitability for enhancing proactive fraud detection efforts in e-wallet platforms.

These results can be interpreted through the lens of the proactive fraud detection framework adopted in this study. The framework posits that effective financial crime prevention requires anticipatory, data-driven systems rather than reactive rule-based mechanisms (ACFE, 2024; Hasan, 2024). Prophet's superior performance in capturing weekly seasonality particularly the weekend spikes linked to leisure-time gambling and football match schedules demonstrates precisely the kind of anticipatory capability that this theoretical framework advocates. By modeling the seasonality component s(t) and the holiday effect h(t) in its additive decomposition, Prophet operationalizes the proactive detection principle: it identifies when high-risk periods will occur before they happen, enabling preemptive resource allocation rather than post-hoc investigation.

Conversely, ARIMA's slightly weaker performance illustrates the limitations that the proactive framework warns against. ARIMA's assumption of stationarity and its reliance on linear autoregressive patterns make it fundamentally a reactive model it extrapolates from recent past values but cannot incorporate external event-driven signals such as holidays or sports tournaments. This aligns with Hasan's (2024) argument that systems which cannot autonomously adapt to new patterns will inevitably fall behind evolving fraud strategies.

Connection to Existing Literature

The results align with studies that highlight limitations of traditional models like ARIMA, which struggle with non-linear trends and irregular fluctuations. Facebook Prophet, on the other hand, is well-suited for forecasting real-world time series with multiple seasonalities, holidays, and changepoints. This supports findings by Taylor & Letham (2018) and others, who

advocate Prophet's flexibility and accuracy for complex business forecasting tasks.

More specifically, the finding that Prophet achieved lower RMSE and MAE than ARIMA is consistent with the comparative analysis by Kwarteng (2024), who reported similar Prophet advantages when forecasting datasets with strong seasonal behavioral patterns. Likewise, Yadav (2022) found that Prophet outperformed ARIMA in time series prediction tasks characterized by multiple overlapping seasonalities, which directly parallels the weekly and holiday-driven patterns observed in the present study's gambling transaction data.

The observed weekend spikes in flagged transactions peaking on Saturdays and Sundays corroborate the behavioral patterns reported by Husainah et al. (2023), who noted that online gambling activity in Indonesia tends to concentrate during leisure periods and around major sporting events. The present study extends this observation by demonstrating that Prophet's s(t) seasonality component can quantitatively capture these weekly cycles, providing an actionable forecasting signal rather than merely a descriptive observation.

Furthermore, the finding that ARIMA performed adequately for general trend modeling but struggled with event-driven fluctuations is consistent with the observations of Moschini et al. (2021), who reported that ARIMA is reliable for detecting linear anomalies in transactional data but limited when confronted with complex seasonal effects or abrupt structural changes. The present study confirms this limitation in the specific context of Indonesian e-wallet gambling transactions, where the interplay of holidays, football matches, and payday cycles creates precisely the kind of multi-layered seasonality that ARIMA is not designed to handle.

The study's results also support the broader argument advanced by the ACFE (2024) and Sidauruk (2024) that organizations adopting analytics-based fraud detection achieve faster response times and greater detection accuracy. By demonstrating that Prophet can forecast gambling transaction spikes with an RMSE as low as 1.29 on daily data, this study provides concrete empirical evidence that time series forecasting when properly configured with domain-specific regressors can serve as a practical tool for the proactive detection paradigm that these institutional frameworks advocate.

Explanation of Unexpected Findings

Even though the model already included regressors for football matches, holidays, and payday windows, it still slightly underestimated some short-term spikes in gambling activity. Prophet, while adept at modeling planned seasonal and event effects, can still underperform when faced with truly unplanned exogenous shocks such as flash promotions or sudden viral trends that weren't captured by the regressors. Prophet's own guidelines acknowledge that in environments with unpredictable "shocks," it benefits from additional external variables or post-hoc retraining to improve forecast responsiveness. Future improvements could include incorporating data on promotions, app notifications, or real-time social media signals to better capture these unexpected surges.

Managerial Implications

From a managerial perspective, using a Prophet-based forecasting tool enables fraud teams in fintech companies to anticipate surges in online gambling activity. This allows for better resource allocation and improved monitoring during high-risk periods. Additionally, it supports compliance departments in producing timely reports for regulators like Bank Indonesia and Komdigi, enhancing overall organizational responsiveness and transparency.

Impact of Changepoints and Seasonality on Forecasting

The performance gap confirms that incorporating changepoints and weekly

seasonality captures behavioural subtleties that a naïve 'same weekday last week' rule misses. Although Prophet's default changepoint prior (0.05) balances bias and variance for our low-fluctuation series, its coverage is slightly below nominal, hinting at mild over-confidence. Future work could explore tighter priors or bootstrap intervals to close this gap.

Limitations

Despite its promising results, the study has several limitations. The dataset focused only on verified online gamblers and may not capture broader behavioral patterns among undetected users. Additionally, the model did not include custom regressors such as promotions or media events that could influence gambling behavior. These exclusions may limit the model's generalizability to other contexts or platforms.

Future Research Directions

Future studies could expand on this work by integrating additional exogenous variables into the Prophet model to improve its responsiveness to sudden shifts. Researchers may also explore hybrid approaches combining time series forecasting with classification models to both predict when fraud is likely and who is most at risk. Applying this framework across multiple digital platforms could also provide comparative insights into online gambling behavior across Indonesia's fintech ecosystem.

5. CONCLUSION

This study has demonstrated that both Facebook Prophet and ARIMA are effective tools for forecasting online gambling activity on Indonesian e-wallet platforms. However, Facebook Prophet exhibited slightly better accuracy and adaptability to complex temporal patterns, including weekly seasonality and event-based fluctuations such as holidays and football matches. These strengths make Prophet a more promising candidate for proactive fraud detection systems.

While ARIMA performed well in modeling general trends, it lacked the flexibility to capture nonlinear and irregular patterns associated with gambling behavior. The results suggest that integrating Prophet into existing fraud detection pipelines could enhance early warning capabilities and help fintech companies better prepare for fraud surges.

Nonetheless, the findings are limited by the exclusive focus on verified gamblers and the omission of external variables like promotions or media influences. These limitations may affect the generalizability of the results. Future research should explore hybrid models, include wider datasets, and leverage real-time external signals to improve prediction accuracy. By evaluating and comparing Prophet and ARIMA in a high-risk financial context, this study contributes practical insights for data-driven fraud prevention and reinforces the importance of predictive analytics in securing Indonesia's digital finance landscape.

REFERENCES

Adekoya, A. A., Olaoye, S. A., & Lawal, B. A. (2023). Internal Audit Values and Fraud Detection: An Empirical Analysis. *Asian Journal of Economics, Business and Accounting, 23*(17), 162–172. https://doi.org/10.9734/ajeba/2023/v23i171051.

Alfian, A. (2023). Fraud Analytics Practices in Public-Sector Transactions: A Systematic Review. *Journal of Public Budgeting, Accounting & Financial Management, 35*(5), 685–710. https://doi.org/10.1108/jpbafm-11-2022-0175.

Association of Certified Fraud Examiners (ACFE). (2024). *Occupational Fraud 2024: A Report to the Nations* (13th ed.). Association of Certified Fraud Examiners. https://legacy.acfe.com/report-to-the-nations/2024/.

Betti, N., & Sarens, G. (2020). Understanding the Internal Audit Function in a Digitalised Business Environment. *Journal of Accounting & Organizational Change, 17*(2), 197–216. https://doi.org/10.1108/jaoc-11-2019-0114.

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. *Future Internet, 15*(8), 255. https://doi.org/10.3390/fi15080255.

Dal Pozzolo, A., Caelen, O., Le Borgne, Y. A., Waterschoot, S., & Bontempi, G. (2014). Learned Lessons in Credit Card Fraud Detection from a Practitioner Perspective. *Expert Systems with Applications, 41*(10), 4915–4928. https://doi.org/10.1016/j.eswa.2014.02.026.

Gupta, R. (2019). Data Mining for Fraud Detection: An Overview of Techniques and Applications. *Turkish Journal of Computer and Mathematics Education, 10*(1), 561–567.

Hasan, K. (2024). Adaptive Fraud Detection: Challenges of Traditional Rule-Based Systems in Digital Finance. *Journal of Financial Crime Analytics, 17*(2), 45–58.

Aros, L. H., Molano, L. X. B., Gutierrez-Portela, F., Moreno Hernandez, J. J., & Barrero, M. S. R. (2024). Financial Fraud Detection through the Application of Machine Learning Techniques: A Literature Review. *Humanities and Social Sciences Communications, 11*(1), 1130. https://doi.org/10.1057/s41599-024-03606-0.

Hilal, W., Gadsden, S. A., & Yawney, J. (2022). Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances. *Expert Systems with Applications, 193*, 116429. https://doi.org/10.1016/j.eswa.2021.116429.

Husainah, N., Paulina, J., Misrofingah, M., Pradipta, I. A., Maulana, A. E., & Fahlevi, M. (2023). Determining Factors of Digital Wallet Actual Usage: A New Model to Identify Changes in Consumer Behavior. *International Journal of Data and Network Science, 7*(2), 933–940. https://doi.org/10.5267/j.ijdns.2022.12.017.

Indonesia Business Post. (2024). *Ministry Cracks Down on E-Wallets Used for Online Gambling*. Indonesia Business Post. https://indonesiabusinesspost.com/insider/ministry-cracks-down-on-e-wallets-used-for-online-gambling/.

Islam, S., & Stafford, T. (2022). Factors Associated with the Adoption of Data Analytics by Internal Audit Function. *Managerial Auditing Journal, 37*(2), 193–223. https://doi.org/10.1108/maj-04-2021-3090.

Jurgovsky, J., Granitzer, M., Ziegler, K., Calabretto, S., Portier, P. E., He-Guelton, L., & Caelen, O. (2018). Sequence Classification for Credit-Card Fraud Detection. *Expert Systems with Applications,100*, 234-245.

Komdigi. (2024). *Laporan Tahunan Kominfo dan Digitalisasi Indonesia*. Kementerian Komunikasi dan Informatika Republik Indonesia.

Kwarteng, S. B. (2024). Comparative Analysis of ARIMA, SARIMA and Prophet Model in Forecasting. *Research & Development, 5*(4), 110–120.

Moschini, G., Houssou, R., Bovay, J., & Robert-Nicoud, S. (2021). Anomaly and Fraud Detection in Credit Card Transactions using the ARIMA Model. *Engineering Proceedings, 5*(1), 56. https://doi.org/10.3390/engproc2021005056.

Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The Application of Data Mining Techniques in Financial Fraud Detection: A Classification Framework and an Academic Review of Literature. *Decision Support Systems, 50*(3), 559–569. https://doi.org/10.1016/j.dss.2010.08.006.

Novita, N., & Anissa, A. (2022). The Role of Data Analytics for Detecting Indications of Fraud in the Public Sector. *International Journal of Research in Business and Social Science, 11*(7), 218–225. https://doi.org/10.20525/ijrbs.v11i7.2113.

PPATK. (2025). *Analisis Transaksi Perjudian Online 2024–2025*. PPATK. https://www.ppatk.go.id/.

Sidauruk, D. L. (2024). Data Analytics in Fraud Prevention and Detection by Government Internal Supervisory Apparatuses at Ministries/Institutions/Local Governments: A Mixed-Method Study. *Asia Pacific Fraud Journal, 9*(2), 241–260. https://doi.org/10.21532/apfjournal.v9i2.340.

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *The American Statistician, 72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080.

Thimonier, H., Popineau, F., Rimmel, A., Doan, B. L., & Daniel, F. (2024). Comparative Evaluation of Anomaly Detection Methods for Fraud Detection in Online Credit Card Payments. In *Proceedings of the Ninth International Congress on Information and Communication Technology (ICICT 2024)*, *1011*, 37–48. Springer. https://doi.org/10.1007/978-981-97-4581-4_4.

Undang-undang (UU). (2024). *Undang-undang (UU) Nomor 1 Tahun 2024 tentang Perubahan Kedua atas Undang-Undang Nomor 11 Tahun 2008 tentang Informasi dan Transaksi Elektronik*. Undang-undang (UU).

Yadav, S. (2022). A Comparative Study of ARIMA, Prophet and LSTM for Time Series Prediction. *Journal of Artificial Intelligence Machine Learning and Data Science, 1*(1), 1813–1816.