Forecasting business exceptions in robotic process automation with machine learning

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ABSTRACT

Business exceptions interrupt robotic process automation (RPA) workflows and oblige costly human intervention. This paper explores the application of machine learning (ML) time series forecasting techniques to predict business exceptions in RPA. Using RPA robot logs from a financial service company, we employ ARIMA, SARIMAX, and Prophet statistical models, comparing their performance with ML models such as XGBoost and LightGBM. Furthermore, we explore hybrid approaches that combine the strengths of statistical models with ML techniques, specifically integrating Prophet with XGBoost and LightGBM. Our findings reveal that a hybrid LightGBM model substantially outperforms traditional methods, achieving a 40% reduction in the weighted absolute percentage error (WAPE) when compared to the top-performing statistical model. These results suggest the potential of ML forecasting in optimizing RPA operations through the analysis of log-generated data.

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1. INTRODUCTION

In today's competitive business environment, robotic process automation (RPA) has emerged as a key technology, employing software robots to mimic human interactions with computer systems, and automate repetitive, rule-based tasks [1]. Its impact on cost reduction and productivity gains has driven increasing adoption in companies [2], [3]. However, effective RPA implementation often requires seamless human-robot collaboration, especially when encountering business exceptions situations where bots cannot process transactions due to predefined limitations, needing human intervention [4]–[6]. These exceptions impact RPA automation by reducing productivity and increasing maintenance costs [7], [8]. Effectively managing bot-human interaction when exceptions occur represents a significant challenge in the post-implementation governance of RPA [9]. The current exception handling mechanism is heavily dependent on human operators, presenting an opportunity in automation and efficiency [10].

While existing research demonstrates the application of specific artificial intelligence (AI) techniques for data recognition, extraction, and classification [11], there remains a significant gap concerning the application of AI functionalities to improve process efficiency within RPA [12], [13]. AI particularly through time series forecasting techniques, offers a promising solution by predicting potential business exceptions based on historical data trends [14]–[16].

The primary question of this research is to determine whether the modern time series machine learning (ML) techniques can provide a more accurate and reliable forecast of RPA business exceptions than established statistical models. Therefore, this study contributes to existing literature by addressing the gap in understanding how AI can improve RPA process efficiency, by proposing the application of ML time series forecasting techniques to predict business process exceptions within RPA workflows. It is worth noting that other studies have also explored the synergy between ML and RPA, such as Patrício *et al.* [17] who investigated the use of combined ML and RPA for proactive maintenance in an industrial context, and Bavaresco *et al.* [18] who explored employees' perceptions of implementing such a combined solution. As far as we are aware, despite some RPA providers like UiPath [19] integrating ARIMA models into their platforms, the application of ML specifically for business exception prediction remains unexplored, presenting a significant opportunity for enhancing RPA productivity [20].

Specifically, we compare the performance of traditional statistical models (ARIMA, SARIMAX), ML models (XGBoost, LightGBM), and hybrid models (Prophet-XGBoost, Prophet-LightGBM) when applied to business exception logs from real-world RPA implementation. ARIMA is a well-established statistical method widely applied in time series forecasting due to its ability to capture linear relationships within data. However, its inability to model nonlinear patterns has led to the development of extensions such as Seasonal ARIMA (SARIMA) and SARIMAX, which incorporate seasonal components and exogenous variables respectively [21].

ML techniques offer robust alternatives by effectively identifying nonlinear relationships and managing large, complex datasets [22]. Tree-based algorithms, particularly gradient boosting methods like XGBoost and LightGBM, have gained popularity due to their superior performance in various forecasting tasks [23]–[25]. Furthermore, hybrid models that combine statistical and ML approaches, such as Prophet integrated with XGBoost or LightGBM, have shown enhanced ability to handle both linear and nonlinear patterns by decomposing time series data into trend, seasonal, and residual components [26].

Grounded in this context, our contributions are as follows: i) to the best of our knowledge, we are the first to apply ML time series forecasting an AI-driven approach, to enhance efficiency in handling RPA business exceptions; and ii) we provide evidence that ML models outperform traditional statistical methods within this specific RPA context. This article is structured in the following way: it starts with an overview of the research methods employed, followed by a discussion of the results. Finally, it presents the overall conclusions.

2. RESEARCH METHOD

This research uses a dataset from a financial services company with extensive RPA experience, comprising daily business exception logs collected over two years by the RPA orchestrator. The underlying automated processes serve as a crucial bridge, fundamentally connecting data originating from diverse external platforms with the company's established legacy IT systems and office applications. Before automation, these processes were meticulously validated by an in-house team of RPA specialists to ensure they exhibited ideal characteristics, including high transaction volumes, clearly defined rules, and significant manual effort. Ultimately, the final selection of processes for automation was strategically guided by the anticipated full-time equivalent (FTE) savings they promised.

From this set of automated processes, we identified 10 with more than 500 recorded days, a criterion established to ensure sufficient data for robust model training. As shown in Figure 1, our subsequent analysis focused on the automated verification of payments, a single, critical process. This process represents a substantial 58% of all business exceptions recorded, information detailed in Table 1.

The original dataset was enriched with exogenous data such as time features (year, month, day, and weekday), as well as a holiday dummy variable. Figure 2 reveals that the time series exhibits seasonal peaks in exceptions during June and December, a consistent weekday pattern with reduced activity on weekends, and sporadic anomalies in specific weeks throughout the year.

Figure 3 illustrates how the dataset was divided into training, validation, and test samples using the Skforecast [27] time series forecasting python library. The objective was to predict the number of exceptions that would occur over the next 30 days. This 30-day horizon was defined by the financial service company, to support their requirement for a monthly follow-up and review of business exceptions. Training sample included 382 days, followed by 240 days for back testing validation and a 30-day horizon test sample.

In this study, a comprehensive approach to time series forecasting was undertaken by employing a suite of algorithms representing different paradigms: statistical models (ARIMA, SARIMAX and Prophet), tree-based machine learning methods (XGBoost and LightGBM), and a hybrid combination (Prophet-XGBoost and Prophet-LightGBM. ARIMA and SARIMAX models have been widely used for forecasting in diverse fields such as road traffic accidents [28], profit prediction [29] and logistics [30]. Similarly, Prophet has been applied for forecasting business event attendance [31] and sales forecasting [32].

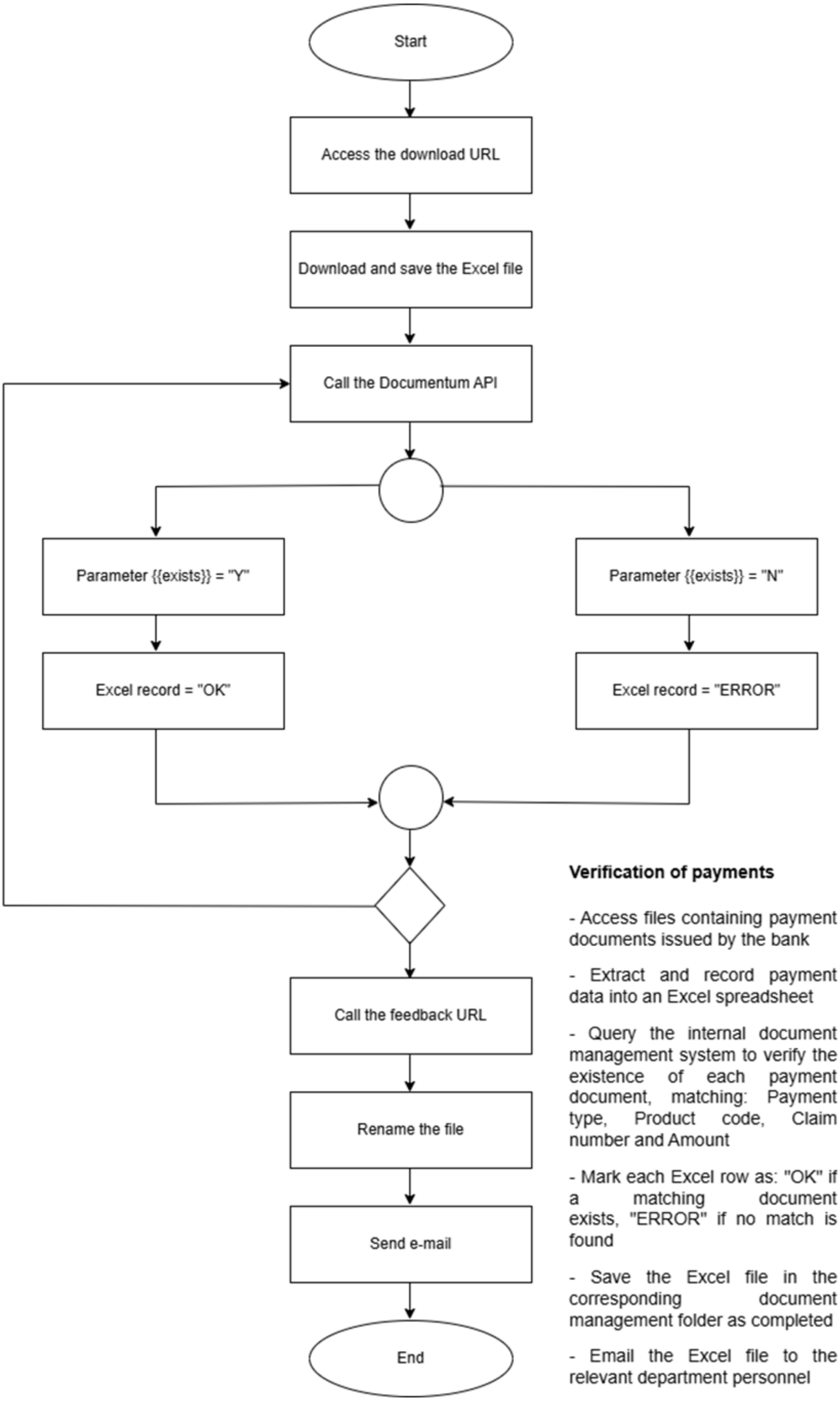

Figure 1. Verification of payments process

Table 1. 10 processes with over 500 days of data

Process	Description	Days	Exceptions	Distribution	Exceptions/Day	Exceptions	Accumulative
Verification of payments	Verification of bank payment documents	723	19,199		26.55	58.07%	58.07%
Policy monitoring	Verification and monitoring of insurance policy	722	7,780		9.94	21.72%	79.79%
Listing of insurance processors	Creating updated lists of insurance processors	722	1,886		2.61	5.52%	85.31%
Insurance cancellation	Cancellation process of one type of insurance	717	1,339		1.87	4.05%	89.36%
Certified letters	Tracking and control of certified letters	722	768		1.06	2.32%	91.68%
Portfolio cleaning	Customer portfolio cleaning	20	721		24.86	2.18%	93.86%
Verification of incomes	Verification of bank income documents	115	690		6.00	2.09%	95.95%
Insurance cancellation for non-payment	Insurance cancellation for non-payment	48	644		13.42	1.96%	97.90%
Insurance registration	Registration process of one type of insurance	718	386		0.54	1.17%	99.07%
Returned transfers	Verification and control of returned transfers	650	307		0.47	0.93%	100.00%

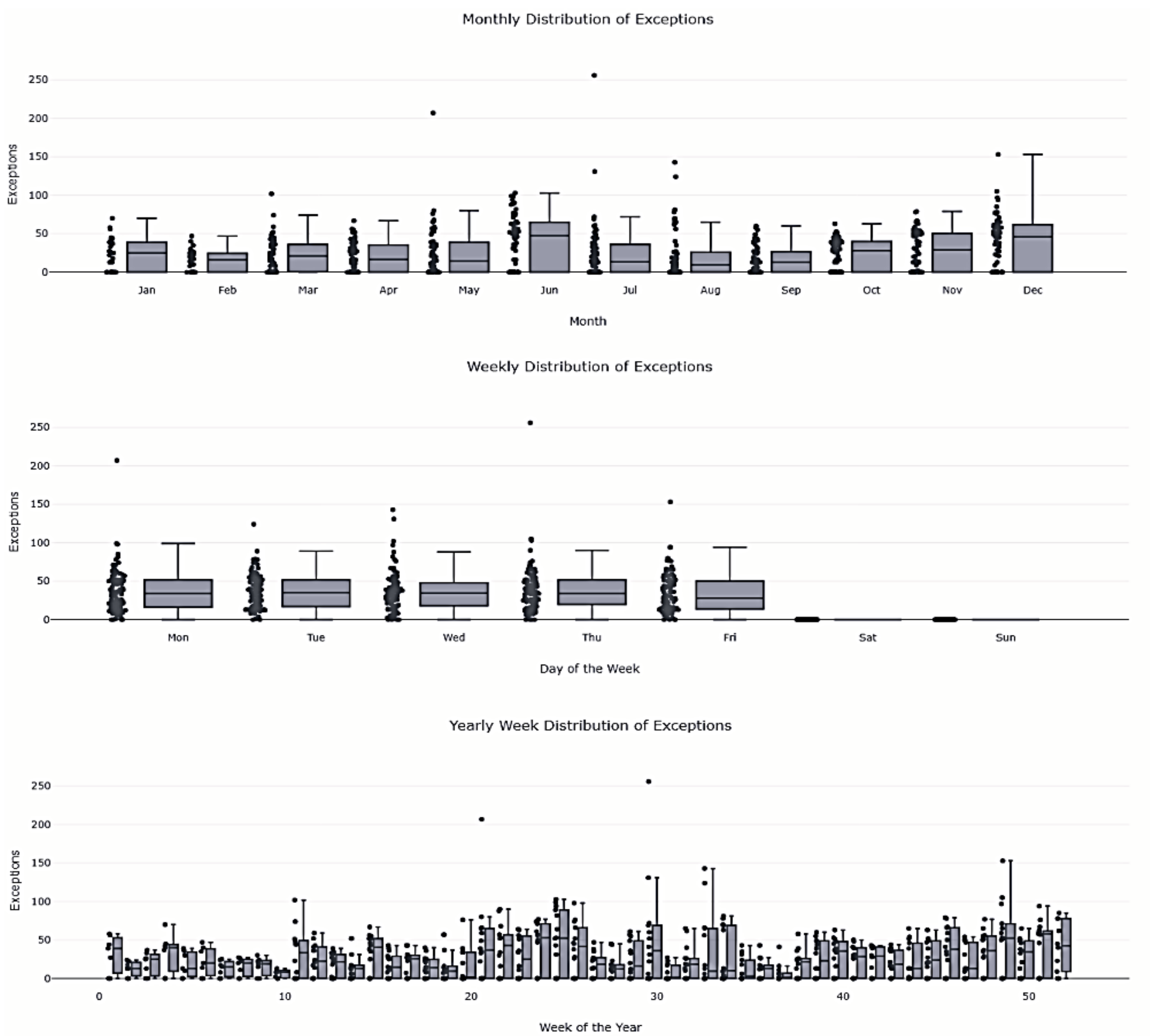

Figure 2. Time series distribution

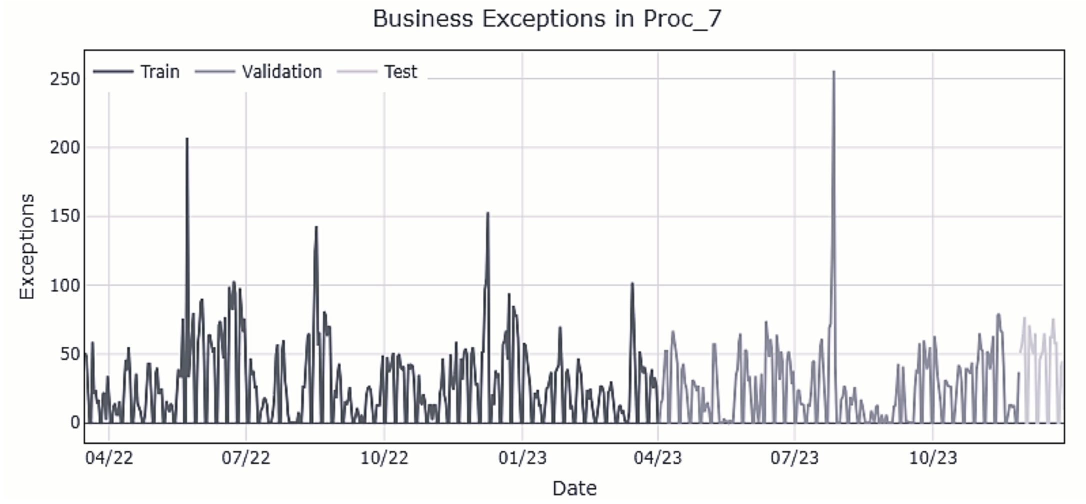

Figure 3. Train, validation, and test samples

Complementing the statistical methods, tree-based ML algorithms, specifically XGBoost and LightGBM, were incorporated. These models are recognized for their ability to effectively model complex, non-linear relationships and interactions within data, which traditional linear models may struggle with [33]. XGBoost and LightGBM have demonstrated strong performance in various prediction tasks, such as stock price prediction [34], fuel consumption [35] and energy load prediction [36].

Furthermore, to potentially improve forecasting accuracy by combining the strengths of different modeling paradigms, a hybrid approach integrating Prophet with either XGBoost or LightGBM was investigated. Hybrid methods are increasingly utilized in time series forecasting as they can capture both linear/seasonal components (addressed by Prophet) and non-linear patterns or residuals (modeled by tree-based methods) [37]. Hybrid approaches combining Prophet and ML models have been successfully applied in heating load forecasting [38] and Strain prediction for historical timber buildings [39].

The forecasting process began with establishing an ARIMA model as the baseline. The ARIMA model was fitted using pmdarima library, enabling automatic selection of the optimal order and seasonal components based on the training and validation data. To refine predictions, a SARIMAX was implemented, incorporating previously calculated exogenous variables into the model. Parameter tuning for the SARIMAX model involved a grid search strategy on the combined training and validation data. Backtesting with refitting was then applied using the best-performing SARIMAX configuration. Additionally, concerning the Prophet model, it was configured with Spanish holiday information and fitted to the prepared dataset.

Complementing the statistical approaches, XGBoost and LightGBM forecasters were explored and refined by using the Skforecast library's tools. Lag features were created incorporating values from the previous 1 through 7 steps. Rolling statistics were also calculated, including moving average and standard deviation over a window of 3 and 5 time steps. Hyperparameter tuning of estimators, depth and learning rates were optimized with Optuna engine [40] The final stage involved a hybrid approach, where Prophet's seasonal and trend insights were fed as features into the ML algorithms, creating Prophet-XGBoost and Prophet-LightGBM models.

3. RESULTS AND DISCUSSION

The performance of each forecasting model was evaluated by the following metrics: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and weighted absolute percentage error (WAPE). We first compared the real values contained in the test dataset with each model's predictions, as shown in Figure 4.

This comparison allowed us to calculate the established metrics, resulting in a ranking of the forecasters' accuracy based on the outlier-resilient and zero-sensitive WAPE metric, as detailed in Table 2. Our findings revealed that ML models exhibit superior performance compared to statistical models. Prophet-LightGBM hybrid forecaster achieved the highest accuracy with a WAPE of 24.45 and an RMSE of 13.83. In contrast, SARIMAX emerged as the best statistical model with a WAPE of 40.91 and an RMSE of 20.85. A comparison between the best ML and statistical models revealed a 40.25% improvement in the WAPE metric in favor of the former. Furthermore, the remaining ML models also outperformed SARIMAX and ARIMA. The superior performance of ML models compared to statistical ones aligns with findings in other research fields, such as customer demand forecasting [41] and rice production prediction [42].

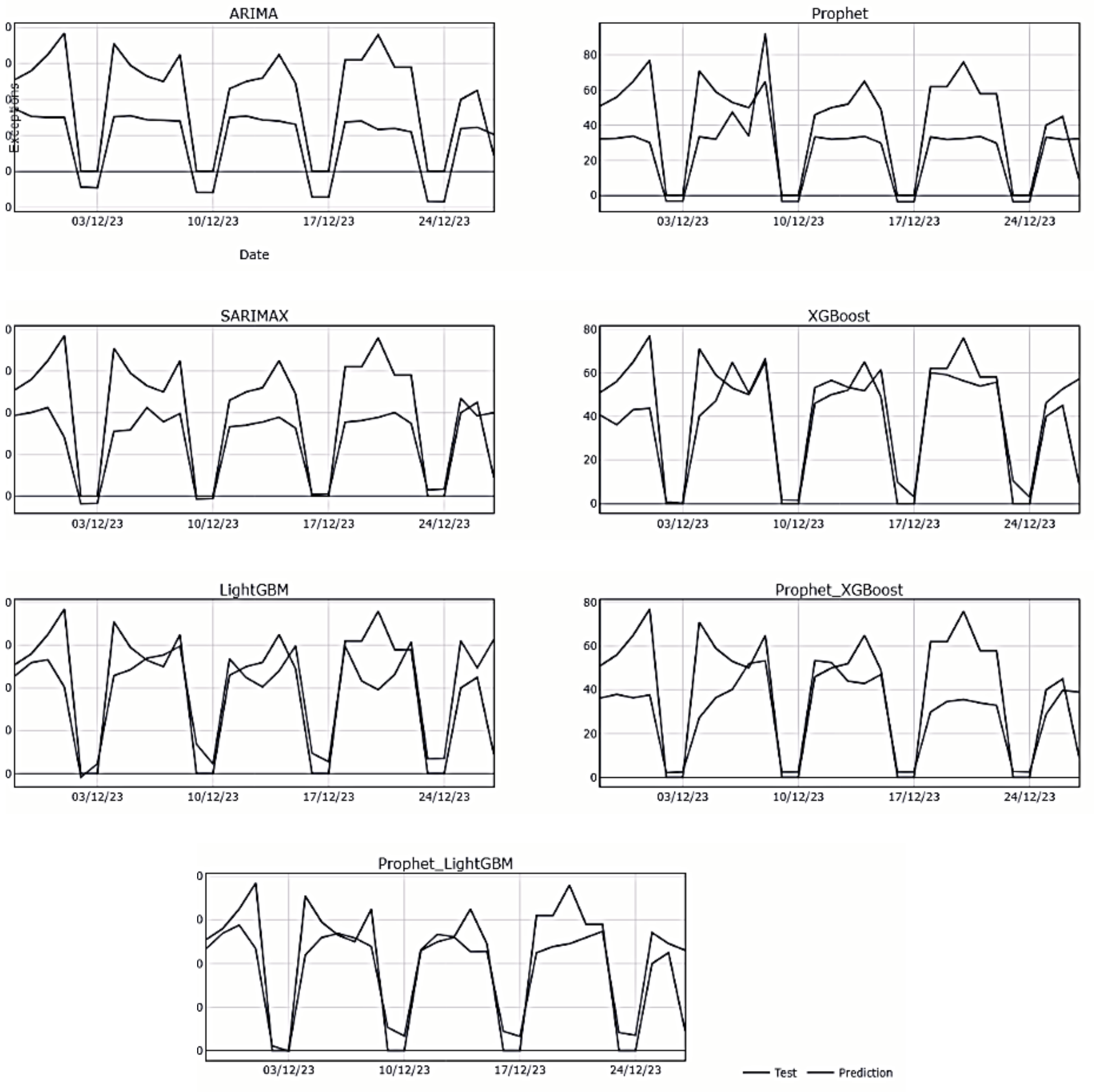

Figure 4. Test sample vs prediction

Table 2. Model performance evaluation

Model name	MAE	WAPE	MSE	RMSE
Prophet-LightGBM	9.933332	24.446264	19.126524	13.829868
XGBoost	10.243320	25.209156	22.769136	15.089445
LightGBM	12.130286	29.853041	28.837858	16.981713
Prophet-XGBoost	15.017549	36.958694	39.918686	19.979661
SARIMAX	16.624254	40.912848	43.477065	20.851155
Prophet	18.667381	45.941053	51.182795	22.623615
ARIMA	24.525257	60.357483	73.465716	27.104560

The practical implementation of a more accurate business exception predictive model integrated in an automated data pipeline from the RPA orchestrator's logs, serves a dual purpose. For planning, the forecast allows managers to anticipate high exception periods, improving operational efficiency and cost. For monitoring, the forecasting tool proactively triggers automation maintenance.

4. CONCLUSION

Our study contributes to the adoption of ML time series forecasting for predicting business exceptions in RPA. By enabling proactive exception management, this approach contributes to cost reduction and productivity improvement in RPA. Furthermore, the proposed methods are broadly applicable to any scenario involving time series forecasting derived from activity logs within the field of business process automation.

This study aimed to enhance business exceptions predictions by comparing traditional statistical models, such as ARIMA and SARIMAX, with advanced ML models like XGBoost and LightGBM, as well as hybrid approaches combining them with Prophet. Our findings demonstrate that ML models significantly outperform traditional statistical models. Specifically, the Prophet-LightGBM hybrid model achieved the highest accuracy, with a 40% improvement over the best statistical model.

As this research adopts a case study approach, it is important to explicitly acknowledge limitations concerning validation. Regarding internal validity, the reliance on one primary RPA process from a single firm requires careful interpretation, as observed patterns might not universally apply. Concerning external validity, the specific context of a homogeneous group of RPA robots within the financial services sector necessitates that future research prioritize replication in diverse RPA environments with similar log structures to establish broader generalizability of these results. Additionally, future research should explore integrating advanced AI techniques to enhance the accuracy of the presented ML models.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Mónica Gago	✓	✓		✓			✓			✓		✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that supports the findings of this study is available from the corresponding author, upon reasonable request.

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