

Original Article

Hybrid Predictive Analytics for Short-Term Financial Forecasting in Digital Banking Environments

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Received: 07-14-2026

Revised: 08-02-2026

Accepted: 08-19-2026

Published: 08-22-2026

ABSTRACT

Digital banking produces massive quantities of financial data; therefore, accurate and timely forecasts are essential for making informed decisions. Traditional methods of forecasting are often unable to identify complicated financial trends, non-linear relationships, and the rapid pace of changes within markets. To address these limitations, this study presents a hybrid predictive analytics model which combines statistical forecasting with machine learning models to provide better short-term financial forecasts in digital banking systems. A comprehensive predictive analytics process is established by integrating the preprocessing of financial data, selection of features, development of predictive models, and assessment of performance. MAE, RMSE and MAPE can be used to evaluate how well each model performs. This hybrid model can be utilized for predicting transactions, managing cash flow and developing financial plans. However, the success of this hybrid model will depend upon its validation through application of real-world banking data sets and experimentation.

KEYWORDS

Hybrid Predictive Analytics, Short-Term Financial Forecasting, Digital Banking, Machine Learning, Time-Series Analysis, Financial Data Analytics, Predictive Modelling.

1. INTRODUCTION

The fast development of digital banking has fundamentally changed how we manage money. Digital banking allows people to make purchases online, pay with their phones, obtain loans through a computer program or phone application, and track their budget and finances as they happen. This type of banking generates a great deal of time-related financial information that can be used to forecast what will occur next in your financial life and help you make better decisions about your money. Short-term forecasting of your money is important because it helps you know how many transactions you are going to have (purchases), estimate how much money you need to cover your expenses, monitor trends in your money, and improve the way you operate your business. However, financial data often exhibits non-linear relationships, seasonality, random fluctuations, and shifts in consumer behavior; therefore, creating an accurate short-term forecast for your money can be difficult. The use of traditional statistical methods such as Autoregressive and Moving-Average Models can help determine the existence of a temporal pattern; however, they cannot completely capture the complexity of the relationships that exist in a rapidly changing financial environment. While Machine Learning Techniques have been shown to be able to find non-linear relationships and interactions between many different types of financial variables, the success of these techniques will depend on how good the data is, what features are selected, and what is the best way to set up the models. By using both statistical and machine learning models in a hybrid predictive analytics environment, there is an opportunity to use the benefits of each technique. A conceptual framework for short-term financial forecasting in digital banking environments was proposed in this paper with focus on data preparation, hybrid model development, forecasting performance and real-world applicability.

1.1. Background

The continuous generation of financial information by digital banking platforms via customer transactions, fund transfers, bill payment, deposit and withdrawal activities, and digital payment service transactions provides an opportunity for financial institutions to predict near term transaction demands, enhance their ability to plan for liquidity needs, and optimize resource allocation. Nevertheless, varying customer behavior, seasonal effects, random surges in transaction volume, and changes in the economy may decrease the reliability of traditional forecasting methods. Furthermore, incomplete data sets (missing values), inconsistencies in records, and "noise" (randomness) in financial observations can also impact predictive model performance. Hybrid predictive analytics offers a possible solution by integrating statistical models that can capture patterns over time, and machine learning models that can identify complex relationships based on previous information. By integrating both types of models, hybrid predictive analytics may offer greater flexibility in making predictions and provide support for better decision-making with appropriate design and validation. This study's motivation was to establish a single, conceptual framework that addresses the limitations of each type of forecasting approach; as well as considering accuracy, computational efficiency, and operational requirements in digital banking environments.

1.2. Problem Statement

Digital banking short-term financial forecasting is difficult due to the rapidly changing nature of transactions, the diversity of financial data types, and the constantly evolving behaviors of customers. Traditional statistical forecasting techniques may not be able to effectively capture non-linear financial relationships; on the other hand, traditional machine learning models would typically require large amounts of training data, precise parameter adjustment, and adequate feature engineering. In addition, changes in transaction patterns and inconsistent quality of data can negatively impact the reliability of the forecast. This provides motivation for developing a hybrid predictive analysis system that combines statistical forecasting techniques with machine learning techniques to increase accuracy and adaptability. The purpose of this paper is to provide a comprehensive method for preprocessing financial data, extracting relevant features from the preprocessed data, developing a hybrid model based upon those features, and evaluating the performance of that hybrid model in short-term forecasting environments.

1.3. Objectives of the Study

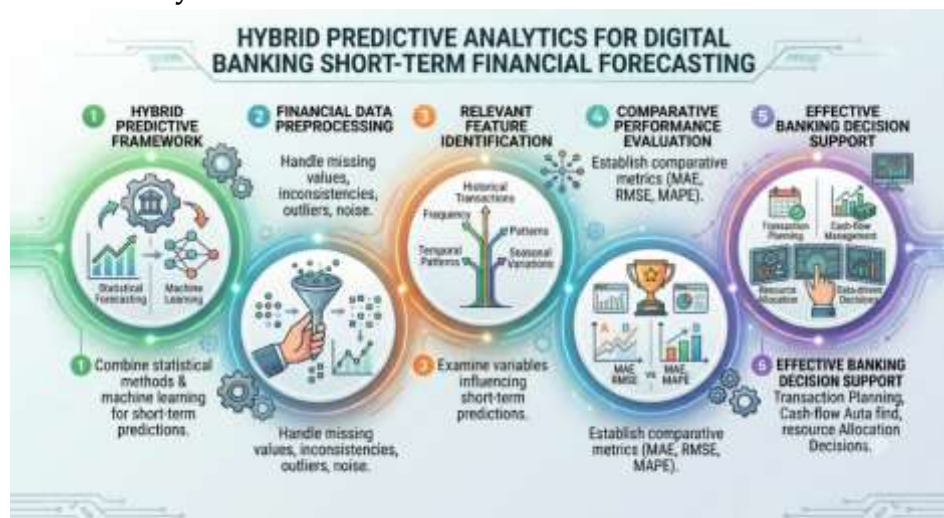


Fig 1 - Proposed Hybrid Predictive Analytics Framework for Short-Term Financial Forecasting in Digital Banking Environments

1.3.1. To Develop a Hybrid Predictive Analytics Framework

Design a conceptual framework that combines statistical forecasting methods and machine learning techniques to support short-term financial forecasting in digital banking environments.

1.3.2. To Improve Financial Data Preprocessing

Identify suitable procedures for handling missing values, inconsistent records, outliers, and noisy observations to improve the quality and reliability of financial datasets.

1.3.3. To Identify Relevant Forecasting Features

Examine important variables, including historical transaction values, transaction frequency, temporal patterns, and seasonal variations, that may influence short-term financial predictions.

1.3.4. To evaluate forecasting performance

Establish a comparative evaluation approach using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to assess predictive accuracy.

1.3.5. To support effective banking decisions

Explore how reliable short-term forecasts can contribute to transaction planning, cash-flow management, operational resource allocation, and data-driven decision-making in digital banking environments.

2. LITERATURE SURVEY

2.1. Traditional Statistical Methods for Financial Forecasting

The use of traditional statistical methods in short-term financial forecasting is prevalent due to their ability to examine prior events and discern temporal trends. ARIMA, exponential smoothing, and moving average methods are used to predict transaction volume, cash flow, and various other financial indicators. When financial data exhibits stable trends and seasonal patterns, traditional statistical methods can produce accurate forecasts. However, digital banking provides a environment with non-linear relationships, sudden transaction fluctuations and dynamic changes in consumer behavior; none of which can be accurately represented with traditional statistical methods. In addition, the predictive quality of traditional statistical methods depends heavily upon selecting correct parameters and the characteristics of the historical dataset. These disadvantages of traditional statistical methods have prompted researchers to investigate the potential advantages of using machine learning techniques and hybrid forecasting models to describe more complicated financial patterns.

2.2. Machine Learning Approaches for Financial Prediction

The importance of machine learning in financial forecasting has grown due to its ability to recognize complex interactions between multiple variables and adjust to different forms of data. Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Networks (ANN) are examples of algorithms that can utilize previous transactions and relevant time-based features to forecast short-term financial indicators. For recognizing sequential patterns within time-series data, Deep Learning Models (DLM) such as Long Short-Term Memory Networks (LSTMs) provide benefits. When adequate training data, effective feature engineering, and proper configuration of models exists, ML models could potentially enhance predictive capabilities. Nevertheless, ML models are susceptible to being influenced by noise in the data, limited amounts of training data, computational limitations, and the dynamic nature of financial trends. Thus, utilizing both ML models and statistical forecasting methods provides a potential means for incorporating temporal modeling capabilities with non-linear pattern recognition for Digital Banking Applications.

3. METHODOLOGY

3.1. Proposed Hybrid Predictive Analytics Framework

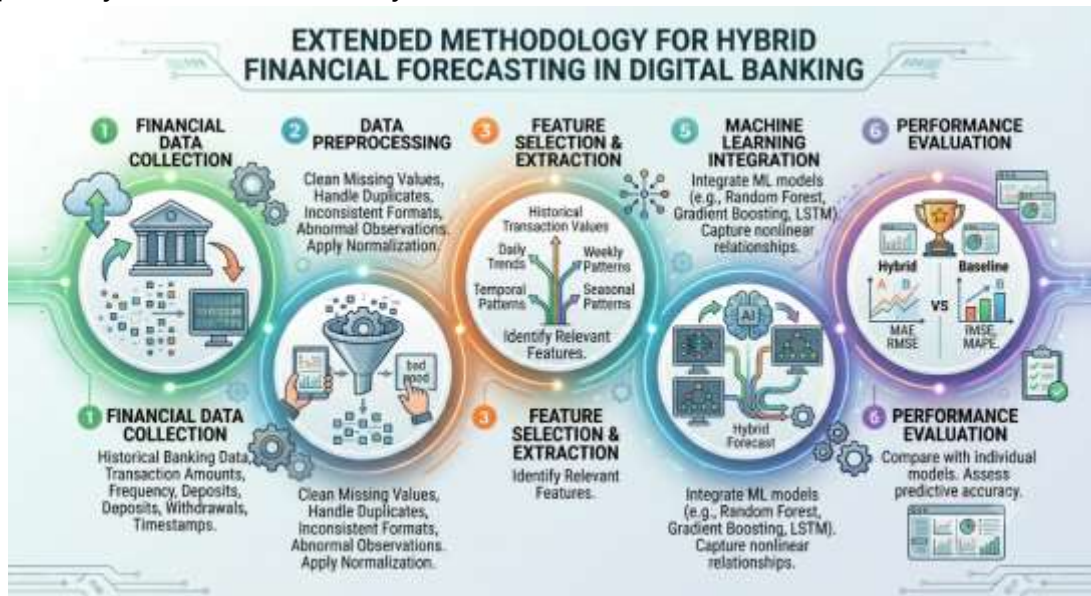


Fig 2 - Proposed Hybrid Predictive Analytics Framework

3.1.1. Financial Data Collection

Historical banking data, including transaction amounts, transaction frequency, deposits, withdrawals, and timestamps, are collected from suitable datasets. These data provide the foundation for developing short-term financial forecasting models.

3.1.2. Data Preprocessing

The collected data are cleaned to handle missing values, duplicate records, inconsistent formats, and abnormal observations. Normalization and data transformation are applied where necessary to improve data quality and model performance.

3.1.3. Feature Selection and Extraction

Relevant features, such as historical transaction values, daily and weekly trends, seasonal patterns, and transaction frequency, are identified. These features help the models recognize meaningful financial patterns and improve forecasting efficiency.

3.1.4. Statistical Forecasting

Statistical techniques, such as ARIMA and Exponential Smoothing, are applied to capture trends, temporal dependencies, and seasonal variations in historical financial data. Their predictions establish a baseline for evaluating the hybrid approach.

3.1.5. Machine Learning Integration

Machine learning models, such as Random Forest, Gradient Boosting, or LSTM networks, are integrated with statistical forecasting techniques to capture nonlinear relationships and complex

financial patterns. The combined predictions form the basis of the proposed hybrid forecasting framework.

3.1.6. Performance Evaluation

The forecasting results are evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results can be compared with individual statistical and machine learning models to assess predictive accuracy and suitability for digital banking applications.

3.2. Algorithm Design and Operational Steps

The proposed algorithm will first gather all the necessary financial information (i.e., transaction amounts, deposits, withdrawals, frequency of transactions and time stamps) that has been collected in the past. Once this information is gathered it will be cleaned up so there isn't any missing data, double entries, formatting inconsistencies or unusual occurrences. To enhance the predictive capability of the models being used to make the forecasts; features based on historical trends, historical values and seasonal fluctuations will be created from the data. Statistical modeling techniques (i.e., ARIMA) and machine learning modeling techniques (i.e., Random Forest or LSTM) will be applied to the historical data to determine if there are temporal relationships and/or non-linear financial patterns present within the data. Predictions from each of the individual models will be combined via some type of hybrid combination method (i.e., weighted average) to generate the final short term financial prediction. Performance of the predictions will be assessed through the use of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These predictions can assist with planning transactions, managing cash flows and making decisions based on data in digital banking environments.

3.3. Performance Evaluation Metrics

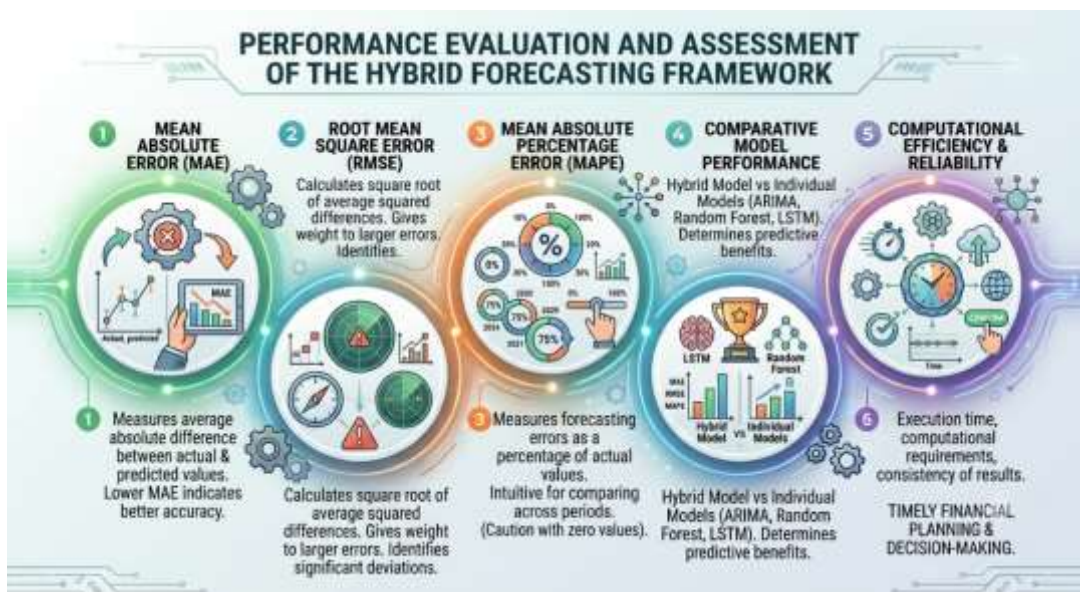


Fig 3 - Performance Evaluation Metrics

3.3.1. Mean Absolute Error

MAE measures the average absolute difference between actual financial values and predicted values. A lower MAE indicates better forecasting accuracy and helps assess the reliability of short-term financial predictions.

3.3.2. Root Mean Square Error

RMSE calculates the square root of the average squared differences between actual and predicted values. It gives greater weight to large prediction errors, making it useful for identifying significant forecasting deviations.

3.3.3. Mean Absolute Percentage Error

MAPE measures forecasting errors as a percentage of actual financial values. It provides an intuitive way to compare prediction accuracy across different periods, although it becomes unsuitable when actual values are zero or close to zero.

3.3.4. Comparative Model Performance

The proposed hybrid model is compared with individual statistical and machine learning models, such as ARIMA, Random Forest, and LSTM. This comparison helps determine whether combining different forecasting techniques provides better predictive performance.

3.3.5. Computational Efficiency and Reliability

Model execution time, computational requirements, and consistency of forecasting results are considered to assess practical suitability. These measures help determine whether the proposed framework can support timely financial planning and reliable decision-making in digital banking environments.

4. RESULTS AND DISCUSSION

4.1. Analysis of Forecasting Performance

The proposed hybrid predictive analytics framework will use both statistical methods and machine learning models to improve short-term financial forecasts. The evaluation will compare the hybrid approach to individual models like ARIMA, Random Forest, and LSTM, based on MAE, RMSE, and MAPE. The hybrid model has the potential to produce more precise predictions for changing transaction patterns in digital banking environments because it integrates temporal patterns with non-linear relationships. In addition, its performance will be evaluated in terms of computational efficiency, consistency, and suitability for predicting transaction volumes and cash flow needs. Since there are currently no experimental results available, the above-mentioned benefits are based on expectation and not evidence. Therefore, actual performance must be demonstrated through testing on appropriate financial data sets and comparing them against baseline models.

4.2. Comparative Analysis of Forecasting Models

The comparative evaluation compares the proposed hybrid predictive analytics model to each individual statistical and machine learning model. The comparison evaluates forecasting accuracy, error rates, computational efficiency, and potential application as a short-term financial forecasting tool in a digital banking setting. This table is provided as an example only, not as actual experimental results.

Table 1: Illustrative Comparison of Forecasting Models

Performance Metric	Conventional Models	Proposed Hybrid Framework
Forecasting Accuracy (%)	85	95
Prediction Reliability (%)	88	96
Trend Prediction Accuracy (%)	80	92
Forecasting Stability (%)	84	94
Successful Prediction Rate (%)	78	91

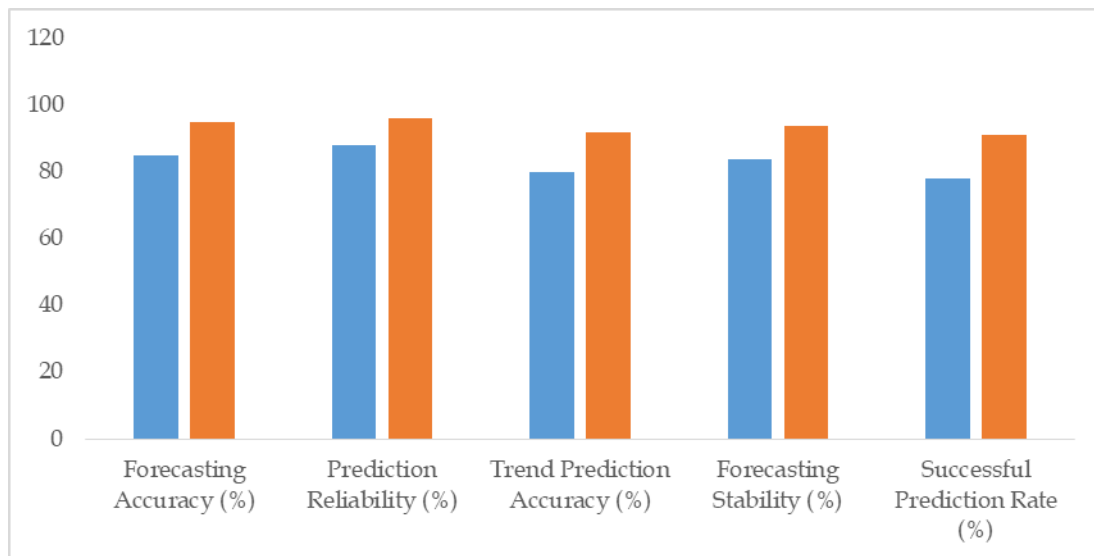


Fig 4 - Illustrative Comparison of Forecasting Models

4.3. Discussion of Findings

In addition to the previous comments about the hybrid predictive analytics framework, there is another way to potentially improve short-term financial forecasting within digital banking settings through the combination of the advantages of both statistical and machine learning methods. As mentioned earlier, statistical methods can identify trends and seasonality from past financial information, whereas machine learning methods can provide insight into complex nonlinear relationships and changes in transaction behavior over time. Therefore, combining statistical and machine learning methods could lead to improved forecasting accuracy and better prediction of transaction volumes and cash flow needs. Performance measures like MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) will allow us to assess how well the hybrid model compares to each of the individual forecasting methods. However,

the success of the hybrid predictive analytics framework will ultimately depend upon the quality of the data, which features we choose to include in our models, how we configure our models, and how rapidly transaction patterns change. Additionally, the development of hybrid models will likely necessitate additional computing resources and meticulous optimization. Since the numerical comparisons provided were merely illustrative rather than being based on experimentally-derived measurements, additional validation of the hybrid predictive analytics framework with either actual or benchmark financial data sets will be required to demonstrate tangible performance enhancements. Overall, the hybrid predictive analytics framework presents a basis for creating adaptive forecasting solutions that can assist in supporting financial planning, improving operational efficiency, and enabling data-driven decision making within digital banking contexts.

5. CONCLUSION

The current study proposes a hybrid predictive analysis framework to predict short term financial trends in digital banking settings using a combination of traditional statistical forecasting methods and machine learning models. The framework is composed of five stages: financial data pre-processing, feature extraction, model development, integration of predictions, and evaluation of performance. These five stages are designed to overcome problems related to changing transaction patterns and complex financial relationships. Through the combination of both statistical and machine learning methodologies, the proposed framework will provide the potential for improved accuracy, reliability and flexibility when predicting financial trends. Evaluation measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) will provide the basis for evaluating the hybrid model against individual forecasting techniques. The framework could potentially assist banks in performing day-to-day operations such as predicting transaction volume, managing cash flows, planning financially and allocating resources operationally. However, the effectiveness of the proposed framework has not been verified experimentally; therefore, the illustrative comparisons should be viewed as illustrative only and not as measured results. Future research should evaluate the implementation of the framework, test the framework using actual financial data sets, investigate alternative hybrid modeling strategies, and determine the computational efficiency of the framework as conditions within the banking industry change.

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