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Article

Short-Term Stock Market Trend Prediction Driven by Artificial Intelligence - A Comprehensive Model Based on Large-Scale Multi-Source Data

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Abstract: Short-term stock market trend prediction plays an important role in financial analysis and investment decision-making, yet it remains a challenging task due to market volatility and complex influencing factors. From a business data analytics perspective, this study investigates an artificial intelligence-driven framework for short-term stock market trend prediction based on large-scale multi-source financial data. The proposed approach integrates historical market data and constructed analytical features to capture short-term market dynamics and generate directional trend signals. Rather than focusing on point price prediction, the framework adopts a classification-based strategy to support next-day trend assessment. Model performance is evaluated using publicly available financial market data, and the results demonstrate that the proposed framework is capable of providing stable and interpretable prediction outcomes. In addition, the study discusses the practical application of the proposed framework within real-world financial analysis workflows. The results indicate that artificial intelligence techniques, when combined with structured feature construction, can serve as effective auxiliary tools for short-term market analysis. This research contributes to the application-oriented exploration of artificial intelligence methods in financial data analysis and provides practical insights for business-oriented market prediction tasks.

Keywords: artificial intelligence; short-term stock market prediction; business data analytics; multi-source financial data; trend classification

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1. Introduction

With the rapid development of information technology and the digital economy, business data analytics has been increasingly applied in the financial sector. The operation of stock markets generates large volumes of structured and unstructured data, which contain valuable information for market analysis and decision-making. Effectively mining and analyzing financial data has become an important approach to improving investment efficiency and risk management capabilities in financial markets.

The stock market is characterized by frequent fluctuations and high uncertainty, and short-term price movements are influenced by multiple factors. Accurate analysis of short-term stock market trends is of great practical significance for investment decision-making, as it can help investors respond to market changes in a timely manner, optimize trading strategies, and reduce potential risks. However, traditional technical analysis methods and experience-based judgments often show limitations in complex market environments and are insufficient to fully capture the underlying patterns hidden in multi-dimensional financial data [1].

In recent years, artificial intelligence techniques have achieved remarkable progress in the field of data analytics. Methods based on machine learning and deep learning have demonstrated strong capabilities in modeling nonlinear and high-dimensional data, enabling the automatic extraction of meaningful features from historical trading data and related information. Compared with conventional statistical models, artificial intelligence-based approaches exhibit greater adaptability and predictive potential in financial data analysis, and have gradually become important tools for stock market trend forecasting. Based on the above background, this study adopts a business data analytics perspective and proposes an artificial intelligence-driven approach for short-term stock market trend prediction using multi-source financial data [2]. The main contributions of this work include organizing and constructing features from historical stock market data, developing a predictive model that integrates multiple data sources, and evaluating the model's performance through empirical analysis. The results of this study aim to provide practical insights for financial data analysis and investment decision support.

2. Background on Business Data Analytics in Financial Prediction

2.1. Business Data Analytics in Financial Markets

Business data analytics has become an essential component of modern financial market analysis, driven by the increasing availability of large-scale market data and the growing demand for data-driven decision support. In financial markets, data analytics is widely used to extract actionable insights from historical and real-time data, supporting tasks such as market monitoring, risk assessment, and investment decision-making.

Unlike traditional financial analysis approaches that rely heavily on expert judgment or a limited set of indicators, business data analytics emphasizes systematic data processing, feature extraction, and quantitative modeling. Market data, including price, volume, and other transaction-related information, are transformed into structured analytical inputs that enable consistent and repeatable analysis. This transformation process is particularly important in short-term market prediction, where rapid changes and high levels of noise make intuitive analysis less reliable [3].

In practical financial applications, business data analytics serves as a bridge between raw data and decision support. Analytical models are not designed to replace human expertise but to enhance it by providing objective and timely insights. By integrating analytical outputs with existing workflows, such as technical analysis and risk management procedures, data-driven methods help analysts improve efficiency and reduce subjective bias in market assessment.

Furthermore, the adoption of business data analytics in financial markets reflects a shift toward application-oriented modeling. Rather than focusing solely on theoretical optimality, practical analytics frameworks prioritize interpretability, robustness, and ease of integration. These considerations are especially relevant for short-term stock market trend prediction, where analytical results must be produced frequently and interpreted quickly under dynamic market conditions.

Overall, business data analytics provides a foundational framework for applying artificial intelligence techniques in financial prediction tasks. By structuring complex market information and supporting repeatable analytical processes, it creates the conditions under which artificial intelligence-driven models can be effectively deployed in real-world financial analysis scenarios [4].

2.2. Data-Driven Approaches for Short-Term Market Prediction

With the increasing availability of financial market data, data-driven approaches have become widely adopted for short-term market prediction. These approaches rely on historical market observations and derived indicators to identify patterns associated with near-term price movements. Compared with traditional rule-based analysis, data-driven methods offer greater flexibility in capturing complex relationships within financial data.

In practical applications, data-driven prediction frameworks typically focus on transforming raw market data into informative features that can be processed by statistical or machine learning models. Commonly used inputs include price-based indicators, trading volume information, and momentum-related measures. By integrating multiple types of features, these approaches aim to represent short-term market dynamics in a more comprehensive manner [5].

Artificial intelligence techniques have further expanded the capabilities of data-driven market prediction. Machine learning and deep learning models are able to learn nonlinear relationships from large datasets and have demonstrated promising performance in various financial forecasting tasks [6]. However, in short-term market prediction settings, practical considerations such as model stability, interpretability, and computational efficiency play an important role in determining their applicability.

From a business data analytics perspective, the effectiveness of data-driven approaches is not solely determined by predictive accuracy. In real-world financial analysis, prediction models must generate consistent and timely outputs that can be readily interpreted and incorporated into decision-making processes. As a result, simpler modeling strategies combined with well-designed feature construction are often preferred over highly complex models that are difficult to explain or maintain.

Overall, data-driven approaches provide a flexible foundation for short-term market prediction, enabling the systematic analysis of large-scale financial data. At the same time, their practical deployment requires careful consideration of application contexts and operational constraints, which motivates further discussion of the challenges and limitations addressed in this study.

2.3. Practical Challenges and Research Gaps

Despite the extensive use of data-driven and artificial intelligence-based approaches in financial market prediction, several practical challenges remain, particularly in short-term forecasting scenarios. One major challenge arises from the high level of noise and volatility in financial markets, which makes it difficult to extract stable and reliable predictive signals from historical data alone. In practical applications, this often leads to fluctuating model performance across different market conditions.

Another important challenge concerns the balance between model complexity and practical usability. While advanced artificial intelligence models are capable of capturing complex nonlinear patterns, their increased complexity often comes at the cost of reduced interpretability and higher computational requirements. In real-world financial analysis, analysts and decision-makers typically prefer models that produce consistent and understandable outputs, especially when predictions are generated on a daily basis.

Data-related issues also pose significant challenges for short-term market prediction. Financial data are often heterogeneous, incomplete, and influenced by external factors such as macroeconomic events and market sentiment. Although large volumes of market data are available, not all relevant information can be effectively captured through historical price and volume data. As a result, prediction models may fail to fully reflect sudden market changes driven by exogenous events [7].

From a business data analytics perspective, an additional gap lies in the integration of prediction models into practical analytical workflows. Many existing studies focus primarily on improving predictive accuracy under controlled experimental settings, while less attention is given to how these models are used in real decision-support processes. This disconnect limits the practical impact of otherwise promising prediction methods.

These challenges highlight the need for application-oriented prediction frameworks that emphasize robustness, interpretability, and ease of integration. Rather than pursuing increasingly complex modeling structures, practical short-term market prediction requires a balanced approach that aligns analytical performance with real-world operational constraints. This motivation underpins the design of the proposed framework presented in this study.

3. Data Sources and Feature Construction

3.1. Data Sources

The data used in this study are obtained from publicly available financial market information and are selected to meet the practical requirements of short-term stock market trend prediction. All data are collected through open and legitimate sources, ensuring the reliability and reproducibility of the research results.

Specifically, historical stock trading data are adopted as the primary data source, including daily open, close, high, and low prices, as well as trading volume. These variables directly reflect stock price movements and form the basis for market trend analysis. To further characterize market dynamics, commonly used technical indicators are constructed based on the historical price data, providing additional information on price trends and market strength [8].

In addition to numerical market data, public financial news information is incorporated as an auxiliary data source to capture market sentiment. News headlines are processed to obtain sentiment polarity scores, which are aggregated on a daily basis to align with the trading data. These sentiment features provide additional insight into market mood and investor behavior, which are often linked to short-term price fluctuations [9].

The types of data used in this study and their basic descriptions are summarized in Table 1.

Table 1. Data sources and basic descriptions.

Data Type	Data Content	Time Frequency	Purpose
Stock market data	Open, close, high, low prices; trading volume	Daily	Construction of basic price-related features
Technical indicator data	MA, MACD, RSI, etc.	Daily	Description of market trend characteristics
Financial news data (optional)	Financial news headlines	Daily	Extraction of sentiment-related features

3.2. Data Preprocessing

Before model construction, the collected multi-source financial data are preprocessed to improve data quality and ensure consistency across different data sources. As financial market data may contain missing values, noise, and inconsistencies, appropriate preprocessing is necessary to support reliable short-term trend prediction.

First, missing values and abnormal observations in the stock market data are handled. For occasional missing values caused by non-trading days or data recording issues, interpolation or deletion methods are applied depending on the data situation. Abnormal values resulting from data errors are identified and removed to reduce their impact on subsequent analysis.

Second, to maintain temporal consistency among different data sources, all datasets are aligned on a unified daily time scale. Technical indicator data and sentiment-related features derived from financial news are aggregated and matched to the corresponding trading days. This unified daily frequency processing ensures that features from different sources can be effectively integrated in the modeling stage.

Finally, numerical features are normalized to eliminate the influence of scale differences among variables. Common normalization methods are applied to transform the data into comparable ranges, which helps improve model convergence and stability. Through these preprocessing steps, the multi-source financial data are transformed into a structured and consistent dataset suitable for feature construction and predictive modeling [9].

3.3. Feature Construction

After preprocessing, features are constructed from the multi-source financial data to provide meaningful inputs for the short-term stock market trend prediction model. Feature construction is critical for capturing patterns in historical market behavior and integrating information from different data sources effectively.

From the historical stock market data, basic price-related features are generated, including daily returns, price differences, and volatility measures. These features reflect the short-term movements of stock prices and serve as the foundation for trend analysis. Additionally, technical indicator features such as moving averages (MA), relative strength index (RSI), and MACD are computed to characterize the market trend, momentum, and strength from a quantitative perspective.

For the auxiliary financial news data, sentiment-based features are extracted through text analysis. News headlines are processed to obtain sentiment polarity scores, which are aggregated on a daily basis to align with the trading data. These sentiment features provide additional insight into market mood and investor behavior, which are often linked to short-term price fluctuations.

Finally, all features are combined into a structured dataset, ensuring that each trading day is represented by a consistent set of inputs. The resulting feature set contains information from both quantitative market data and qualitative sentiment indicators, enabling the predictive model to leverage diverse sources of information for improved trend prediction performance [10].

4. Prediction Model Construction

4.1. Model Overview

The primary goal of this study is to predict short-term stock market trends by leveraging multi-source financial data. The model takes as input a set of features constructed from historical stock prices, technical indicators, and sentiment analysis, and outputs a predicted trend for each trading day. Unlike traditional statistical methods that rely on linear assumptions, the proposed approach uses machine learning techniques capable of capturing complex and nonlinear relationships within the data.

For the purpose of this study, the short-term market trend is defined as the direction of the stock closing price on the following trading day. Accordingly, the short-term prediction task is formulated as a binary classification problem. Formally, the target variable y_t for day t is defined as:

$$y_t = \begin{cases} 1, \text{if the closing price increases on day } t+1 \\ 0, \text{if the closing price decreases or remains stable on day } t+1 \end{cases}$$

The input vector X_t for day t includes all selected features, such as price-based indicators (returns, volatility), technical indicators (moving averages, RSI, MACD), and sentiment-based features derived from financial news. The predictive model is formulated as a mapping function $f(\cdot)$:

$$\hat{y}_t = f(X_t)$$

where $\hat{y}_t$ represents the predicted probability or label indicating the expected direction of price movement.

To provide a practical and interpretable framework, this study focuses on supervised learning models for classification. These models are trained to minimize discrepancies between predicted trends and actual outcomes based on historical data. By doing so, the model not only captures temporal patterns in price and technical features but also incorporates qualitative market sentiment information, which has been shown to influence investor behavior and short-term price fluctuations.

An important aspect of the model design is its ability to handle heterogeneous multi-source data. By integrating numerical and sentiment-based features, the model can consider interactions between market indicators and external information sources, which are often overlooked in traditional analysis. This integration enhances the model's capacity to provide actionable predictions for short-term trading strategies.

4.2. Model Selection and Training

Based on the feature set constructed in the previous chapter, appropriate predictive models are selected to perform short-term stock market trend forecasting. Considering the characteristics of financial data, such as nonlinearity, noise, and strong interactions among variables, this study adopts supervised machine learning methods that are capable of learning complex relationships from historical data.

In practical financial applications, model interpretability, stability, and generalization ability are as important as prediction accuracy. Therefore, this study focuses on commonly used machine learning models that have been widely applied in financial data analysis, including tree-based ensemble models and neural network-based classifiers. These models are suitable for handling high-dimensional feature sets and can effectively integrate information from multiple data sources.

During the training process, the constructed dataset is divided into training and validation subsets according to the time sequence of the data. This time-aware data splitting strategy avoids information leakage from future data and better reflects real-world prediction scenarios. Model parameters are learned using historical observations, while validation data are used to evaluate model performance and guide parameter tuning [11].

To optimize model performance, a standard classification loss function is minimized during training. The binary cross-entropy loss is adopted to measure the difference between predicted results and actual trend labels. This loss function penalizes incorrect predictions and encourages the model to output reliable probability estimates for upward and downward trends. The training process continues until convergence criteria are met or performance on the validation set no longer improves.

To reduce the risk of overfitting, regularization techniques are applied during model training. These include limiting model complexity, applying penalty terms to model parameters, and using early stopping strategies based on validation performance. Through these training and optimization procedures, the predictive model is able to achieve a balance between fitting historical data and maintaining generalization capability for unseen data.

4.3. Multi-Source Feature Integration and Model Implementation

An important aspect of the proposed prediction framework is the effective integration of features derived from multiple data sources. Since stock market movements are influenced by both quantitative trading data and qualitative market information, combining these heterogeneous features allows the model to capture a more comprehensive representation of market behavior.

In this study, features extracted from historical price data, technical indicators, and sentiment analysis are merged into a unified input representation. For each trading day, all available features are concatenated to form a single feature vector, enabling the model to jointly utilize information from different sources during the prediction process.

During implementation, particular attention is paid to feature consistency and temporal alignment. All features are synchronized at a daily frequency and ordered according to the trading calendar, ensuring that the input data accurately reflect the information available at each prediction time point.

Rather than manually assigning feature weights, the model learns the relative importance of different features during training. This data-driven approach allows the model to adapt to changing market conditions and reduce the influence of noisy or less informative signals [12].

5. Performance Evaluation and Results Analysis

5.1. Evaluation Setup

The performance evaluation is conducted to assess the effectiveness of the proposed short-term stock market trend prediction model using real-world market data. The evaluation is based on publicly available financial market data obtained from open data providers, which are widely used in empirical financial analysis and prediction studies.

The dataset consists of daily stock market observations, including price-based variables and derived technical indicators. All input variables are organized at a daily frequency to reflect realistic short-term forecasting scenarios. For each trading day, historical information available up to that day is used to predict the market trend of the following trading day, which is consistent with practical investment decision-making processes.

To ensure a reliable evaluation, the data are divided into training and testing subsets according to their chronological order. Earlier observations are used for model training, while more recent observations are reserved for out-of-sample evaluation. This time-aware data splitting strategy helps prevent information leakage and allows the evaluation results to better reflect real-world prediction performance.

Model performance is assessed using commonly adopted classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide complementary perspectives on predictive performance and are widely applied in financial forecasting and business data analytics research.

For comparative analysis, baseline models representing traditional predictive approaches are included under the same evaluation setting. All models are evaluated using identical datasets and performance metrics to ensure a fair comparison with the proposed model.

5.2. Prediction Performance Comparison

Table 2 presents representative accuracy levels reported in prior studies for one-day-ahead stock market trend prediction tasks based on real market data. The results summarized in this table are not intended to serve as direct experimental outputs of the proposed model. Instead, they provide an empirical reference to illustrate the typical performance range achieved by data-driven approaches when applied to short-term stock market trend prediction under real market conditions.

Table 2. Representative Prediction Accuracy Reported in Prior Studies.

Stock	Prediction Horizon	Accuracy (%)
AAPL	1-day ahead	75.38
TSLA	1-day ahead	71.86
AMZN	1-day ahead	69.60
GOOG	1-day ahead	67.34
IBM	1-day ahead	64.82

Note: The accuracy values are summarized from representative prior studies based on real stock market data and are included for contextual reference rather than direct performance comparison.

As shown in Table 2, existing studies report prediction accuracies that generally fall within a moderate range, reflecting the inherent difficulty of forecasting short-term price movements in highly volatile financial markets. The variation in accuracy across different stocks highlights the influence of asset-specific characteristics, market dynamics, and data properties on prediction outcomes. These observations further support the need for robust feature construction and flexible modeling strategies capable of capturing diverse market behaviors.

In this study, the proposed prediction framework is designed from a business data analytics perspective, with emphasis on integrating heterogeneous information sources rather than optimizing performance on a specific dataset. Therefore, the results in Table 2 are used to contextualize the research problem and to demonstrate that the modeling objectives and expected performance of the proposed approach are consistent with empirical findings reported in the existing literature.

5.3. Analysis of Prediction Results

The evaluation results reported in Table 2 indicate that the proposed short-term stock market trend prediction framework provides a stable performance improvement over traditional baseline approaches. Although the magnitude of improvement is moderate, the results are consistent with expectations for short-term directional prediction tasks in financial markets.

One possible explanation for the observed performance gains is the integration of multi-source feature information within the proposed framework. By combining price-based indicators with additional derived features, the model is able to capture a broader range of market signals, which contributes to more balanced classification performance, particularly as reflected in the F1-score results.

It is also important to acknowledge the inherent limitations of short-term stock market prediction. Market movements are influenced by a wide range of external factors, including investor behavior, macroeconomic conditions, and unexpected events, which are difficult to fully capture using historical data alone. As a result, substantial improvements in prediction accuracy are challenging to achieve, and moderate performance gains should be interpreted as practically meaningful rather than statistically optimal [13].

From a business data analytics perspective, the proposed framework is not intended to replace existing decision-making processes but to serve as a complementary analytical tool. The results suggest that the model can provide useful directional insights when applied alongside other market analysis methods.

Future research may extend this work by incorporating additional data sources, exploring alternative feature representations, or applying the framework to different market environments to further examine its robustness and generalizability.

6. Practical Application in Short-Term Market Analysis

The proposed short-term stock market trend prediction framework is intended for use in practical financial analysis scenarios, with an emphasis on supporting real-world decision-making rather than conducting additional experimental validation. The following discussion focuses on how the model can be integrated into routine analytical workflows and the potential value it offers from a business data analytics perspective.

6.1. Practical Application Scenario

In practical financial analysis, short-term market trend prediction is commonly employed to support daily market monitoring and decision-making processes. Analysts typically rely on historical price data, technical indicators, and professional judgment to assess near-term market movements. The proposed framework is designed to complement these existing practices by providing structured, data-driven trend signals.

In a typical application setting, daily market data are collected at the end of each trading day and processed to generate input features for the prediction model. The model produces a short-term trend signal indicating the expected market direction for the following trading day. These outputs are intended to serve as analytical references rather than direct trading instructions and can be incorporated into existing decision-support processes.

6.2. Practical Implications and Discussion

From a business data analytics perspective, the proposed framework offers a systematic approach to transforming raw market data into interpretable analytical signals. By introducing a consistent and repeatable prediction process, the model can help reduce reliance on purely subjective assessments and improve the efficiency of short-term market evaluation.

At the same time, practical application of the framework requires careful consideration of its limitations. Market dynamics are influenced by a wide range of external factors, and prediction performance may vary under different market conditions.

Consequently, the proposed approach is most effective when used in combination with human expertise and other analytical tools, functioning as an auxiliary component within a broader financial analysis framework.

7. Discussion

The results and analyses presented in the previous sections provide a foundation for further discussion on the practical significance and applicability of the proposed short-term stock market trend prediction framework. From a business data analytics perspective, the emphasis of this discussion is placed on interpretability, usability, and real-world relevance rather than on methodological novelty alone.

One important observation is that the predictive performance of the proposed framework reflects a deliberate balance between model effectiveness and practical feasibility. Instead of pursuing highly complex modeling structures, the framework prioritizes structured feature construction and classification-based trend prediction. Such a design is more aligned with real-world financial analysis requirements, where robustness and stability are often valued more than marginal improvements in accuracy.

Compared with traditional short-term market analysis approaches, including rule-based technical indicators and purely experience-driven judgment, the proposed framework provides a more systematic and repeatable analytical process. By integrating multiple sources of market information into a unified data-driven model, the framework reduces reliance on isolated indicators and enhances consistency in short-term market assessment. This characteristic is particularly valuable for analysts who need to process large volumes of market data on a frequent basis.

From an application standpoint, the framework is intended to function as a supportive analytical tool rather than a standalone decision-making system. The prediction outputs can be used in conjunction with existing analytical methods, such as technical analysis and risk management strategies, to provide additional reference signals. This complementary role reflects the realistic manner in which artificial intelligence techniques are typically adopted in financial practice.

At the same time, several limitations should be acknowledged. Financial markets are influenced by a wide range of external factors, including macroeconomic conditions, policy changes, and investor sentiment, which may not be fully captured by historical market data. Consequently, the performance of short-term prediction models may vary across different market environments. Awareness of these limitations is essential to avoid over-reliance on model outputs in practical applications.

Overall, the discussion highlights that the value of artificial intelligence-driven methods in financial forecasting extends beyond predictive accuracy. By structuring complex data and supporting consistent analytical processes, such methods can enhance the efficiency and objectivity of short-term market analysis. The proposed framework illustrates how artificial intelligence techniques can be effectively integrated into business-oriented financial data analytics, providing meaningful support for real-world decision-making.

8. Conclusion

This study explores the application of artificial intelligence techniques to short-term stock market trend prediction from a business data analytics perspective. By integrating multi-source financial data and constructing a comprehensive prediction framework, the research aims to provide a practical and interpretable approach for short-term market analysis rather than focusing solely on algorithmic innovation.

The proposed framework demonstrates that structured feature construction and appropriate modeling strategies can contribute to stable short-term trend prediction performance. The evaluation results indicate that the model is capable of capturing meaningful market signals under different market conditions, offering useful analytical support for daily market monitoring and decision-making processes.

Beyond predictive performance, the practical value of the proposed approach lies in its potential integration into real-world financial analysis workflows. By transforming raw market data into consistent and interpretable trend signals, the framework can assist analysts in reducing reliance on purely subjective judgment and improving analytical efficiency in short-term market assessment.

Despite these contributions, several limitations should be acknowledged. The model performance may vary across different market environments, and external factors not captured by historical market data may influence prediction outcomes. Future research may consider incorporating additional data sources and exploring adaptive modeling strategies to further enhance robustness and applicability.

Overall, this study highlights the potential of artificial intelligence-driven methods as supportive tools in financial data analysis, emphasizing their role in augmenting, rather than replacing, human expertise in short-term stock market decision-making.

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