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Predicting Stock Prices and Asset Bubbles Using Deep Learning: A Case Study of Nvidia

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Predicting Stock Prices and Asset Bubbles Using Deep Learning: A Case Study of Nvidia and Spotify

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ABSTRACT This study uses a hybrid deep learning model that combines convolutional neural networks, long short-term memory networks and natural language processing to predict Nvidia's stock prices and identify potential asset bubbles. The models are trained on features including technical indicators, trading volume, financial statements, and news sources, and outperformed traditional forecasting methods. The study shows that deep learning models have great potential for financial prediction and could contribute to financial market stability. The findings are significant in the context of Nvidia's emphasis on AI and machine learning, and highlight the importance of incorporating non-traditional data sources into financial prediction models.

INDEX TERMS Stock price, Asset bubbles, Predictive analytics, deep learning

1. INTRODUCTION

An asset price bubble is, loosely speaking, a situation in which the asset price is too high to be justified by fundamentals**[1]**. History abounds with bubbly episodes. Famous examples are the Dutch tulip mania of the 1630s, the South Sea Bubble of 1720 in England, the Japanese real estate and stock market bubble of the 1980s, and the U.S. dot-com bubble of the late 1990s and the housing bubble of the early 2000s, among others. Asset price bubbles occur within larger historical trends involving shifts in industrial structure that cause unbalanced growth. Successfully predicting stock prices and potential asset bubbles helps investors mitigate risks and maximize returns, maintaining financial market stability.

Nvidia is a leading manufacturer of graphics cards for gaming, AI and other scientific applications, and has experienced exponential growth in recent years. With its strong focus on AI and machine learning, Nvidia's stock prices and potential asset bubbles have drawn significant attention within the tech stock market trends. The analysis of Nvidia's market data has the potential to provide valuable insights into the trends of AI and tech industry as a whole.

With the advancement of deep learning technology, researchers have begun employing deep neural network models such as LSTM, MLP, CNN, and GRU to tackle nonlinear prediction problems in stock markets[2]. they have the potential to greatly enhance the reliability of stock market predictions [3]. This study uses a hybrid deep learning model that combines convolutional neural networks, long short-term memory networks and natural language processing to predict Nvidia's stock prices and identify potential asset bubbles.

2. THEORETICAL FOUNDATION

This section outlines the theoretical foundation of the hybrid deep learning model combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Natural Language Processing (NLP) techniques. These components are integrated to predict Nvidia's stock price and identify potential asset bubbles.

A. CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNNs are primarily used for feature extraction from high-dimensional data. In the context of stock price prediction, CNNs can capture spatial dependencies and identify patterns in the data, such as trends in stock prices and trading volumes[2].

a) THEORETICAL CONCEPTS

CNNs utilize convolutional layers to filter input data and identify local features. Each convolution operation involves a filter (or kernel) sliding over the input data, performing element-wise multiplication, and summing the results to generate feature maps.

b) MATHEMATICAL REPRESENTATION

Let **X** be the input matrix (e.g., historical price data), **K** be the kernel matrix, and **Y** be the output matrix (feature map). The convolution operation is defined as:

Equation 1

$$Y(i,j)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}X(i+m,j+n)\cdot K(m,n)$$

Here, $(i,j)(i,j)(i,j)$ represents the position of the output feature map, $M \times N$ is the kernel size, and

$X(i+m, j+n) \cdot K(m,n)$ is the dot product of the overlapping regions of **X** and **K**.

The resulting feature maps are then passed through an activation function and pooling layers to reduce dimensionality while preserving essential features.

B. LONG SHORT-TERM MEMORY NETWORKS (LSTM)

LSTM networks are a type of Recurrent Neural Network (RNN) that effectively model sequential data and capture long-term dependencies[4]. They are widely used for time-series prediction due to their ability to remember information for extended periods.

a) THEORETICAL CONCEPTS

LSTM networks address the vanishing gradient problem of traditional RNNs by introducing memory cells and gating mechanisms. These gates (input, forget, and output) regulate the flow of information, allowing the network to maintain and update memory over time.

b) MATHEMATICAL REPRESENTATION

The LSTM unit consists of cell state C_t, hidden state h_t, input x_t, and gates: input gate i_t, forget gate f_t, and output gate o_t. The equations governing the LSTM cell are as follows:

a) **Forget Gate:** Determines which information to discard from the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

b) **Input Gate:** Decides which new information to add to the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

c) **Cell State Update:** Updates the cell state with the new and retained information.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

d) **Output Gate:** Determines the output based on the updated cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot \tanh(C_t)$$

Here, σ represents the sigmoid activation function, *tanh* is the hyperbolic tangent function, **W** and b denote weight matrices and bias terms, respectively.

C. NATURAL LANGUAGE PROCESSING (NLP)

NLP techniques are employed to extract sentiment and relevant features from textual data sources, such as financial news, social media posts, and company announcements.

By integrating textual analysis, we can capture market sentiment and its influence on stock prices.

a) THEORETICAL CONCEPTS

Textual data is transformed into numerical representations using techniques like word embeddings or more advanced models like BERT (Bidirectional Encoder Representations from Transformers).

Sentiment analysis involves classifying text into positive, negative, or neutral sentiments using pre-trained models or customized classification approaches.

b) MATHEMATICAL REPRESENTATION

Given a text corpus $T = \{t_1, t_2, \ldots, t_n\}$, each text t_i is transformed into a vector representation v_i using an embedding function **E**.

Equation 2

$$v_i = E(t_i)$$

Sentiment scores S_i are derived from these vectors, typically using a neural network classifier:

Equation 3

$$S_i = \text{softmax}(W_s \cdot v_i + b_s)$$

Here, W_s and b_s are the weight matrix and bias for the sentiment classifier.

D. HYBRID MODEL INTEGRATION

The hybrid model combines CNNs, LSTMs, and NLP to leverage both quantitative market data (historical prices, trading volumes) and qualitative textual information (news sentiment). The CNN component processes input data to extract spatial features, which are then passed to the LSTM component to capture temporal dependencies[3]. Concurrently, the NLP module extracts sentiment features from textual data.

a) MATHEMATICAL REPRESENTATION OF HYBRID MODEL

a) Let X_{price} be the price-related data input and X_{test} be the textual data input.

b) The CNN processes X_{price} to produce feature maps F_{cnn}:

Equation 4

$$F_{cnn} = \text{CNN}(X_{\text{price}})$$

c) The LSTM processes the sequential feature maps to generate hidden states H_{lstm}:

Equation 5

$$H_{\text{lstm}} = \text{LSTM}(F_{\text{cnn}})$$

d) The NLP model processes X_{test} to extract sentiment features S_{nlp}:

Equation 6

$$S_{nlp} = \mathrm{NLP}(X_{\text{text}})$$

e) The final prediction **Y** is obtained by combining LSTM outputs with NLP features through a fully connected layer:

Equation 7

$$Y = \sigma(W_{fc} \cdot [H_{lstm}, S_{nlp}] + b_{fc})$$

Here, W_{fc} and b_{fc} are the weight matrix and bias for the fully connected layer, and σ represents the activation function.

3. MATERIALS AND METHODS

A. DATA COLLECTION

a) NVIDIA STOCK PRICES

The historical dataset of NVIDIA stock prices from 1999-01-01 to 2024-08-20 are used. It contains 6434 rows of trading data with several columns: opening price, highest price, lowest price, closing price, adjust price and volume. The data was sourced from Yahoo Finance.

b) NVIDIA FINANCE NEWS

This dataset contains selected financial news articles related to NVIDIA from Yahoo and X (Twitter) from August 2015 to June 2024. The collection and compilation of this dataset focuses on capturing key financial news, market performance insights, strategic business initiatives, and technological advancements that impact these companies[5]. The data covers a range of release dates, providing a temporal view of major events and their potential impact on the market and company valuations.

c) NVIDIA FINANCE DATA

We have collected NVIDIA's financial report data from 2021 to 2024. Financial statements include the company's income statement, balance sheet and cash flow statement, among which the income statement mainly includes the company's operating income, net profit, etc., the balance sheet mainly includes the company's assets, liabilities, etc., and the cash flow statement mainly includes the company's operating cash flow, investment cash flow, financing cash flow, etc. These data can be used to calculate the rate of return, profit margin, and price-earnings ratio[2]. The data was sourced from Yahoo Finance.

d) S&P 500 STOCKS

The Standard and Poor's 500 or S&P 500 is the most famous financial benchmark in the world. This stock market index tracks the performance of 500 large companies listed on stock exchanges in the United States. As of December 31, 2020, more than $5.4 trillion was invested in assets tied to the performance of this index. Because the index includes multiple classes of stock of some constituent companies—for example, Alphabet's Class A (GOOGL) and Class C (GOOG)—there are actually 505 stocks in the gauge. The data was sourced from

Yahoo Finance.

e) HISTORICAL 3-MONTH TREASURY BILL RATES (2000-2023)

Treasury Bills (T-Bills) are short-term government securities with maturities of one year or less. They are sold at a discount from their face value and do not pay interest before maturity. This dataset specifically focuses on the 3-month T-Bill rates, which are commonly used as a risk-free rate benchmark in various financial models and analyses. The 3-month T-Bill rate is considered a reliable indicator of short-term interest rates and economic conditions. It is widely used in the valuation of financial instruments, risk management, and macroeconomic analysis. The data was sourced from Yahoo Finance.

B. INDICATOR CONSTRUCTION

a) TECHNICAL INDICATORS

Technical indicators are mathematical calculations based on historical stock prices, typically used to predict future price movements by analyzing past market data. They help to gauge market sentiment and trend strength.

TABLE I

TECHNICAL INDICATORS

Indicator	Reason for Use	Formula
Moving Average (MA)	Smoothens out price data to identify trends	MA = (P1 + P2 + ... + Pn) / n
Relative Strength Index (RSI)	Measures the speed and change of price movements	RSI = 100 - (100 / (1 + RS))
Bollinger Bands	Measures volatility and relative price levels	BB = MA ± (Standard Deviation * K)

Table 1

b) TRADING VOLUME INDICATORS

Trading volume indicates the number of shares or contracts traded for a security or an entire market within a given period. It helps to understand stock liquidity, investor participation, and market demand.

TABLE 2

TRADING VOLUME INDICATORS

Indicator	Reason for Use	Formula
Volume	Measures the total trading activity	Sum of shares traded
On-Balance Volume (OBV)	Predicts price movements by tracking volume flow	OBV = OBV (previous day) ± Volume
Volume-Weighted Average Price (VWAP)	Reflects the average trading price of the stock over the trading day	VWAP = (Sum of Price * Volume) / Total Volume

Table 2

c) FINANCE STAEMENT INDICATORS

These indicators are derived from the company's financial statements, providing insights into financial health and performance metrics.

TABLE 3

FINANCIAL STATEMENT INDICATORS

Indicator	Reason for Use	Formula
Earnings Per Share (EPS)	Measures profitability per share	EPS = (Net Income - Dividends) / Outstanding Shares
Price-to-Earnings (P/E) Ratio	Assesses stock valuation	P/E = Current Stock Price / EPS
Return on Equity (ROE)	Measures profitability relative to shareholders' equity	ROE = Net Income / Shareholder's Equity

Table 3

d) NEWS SOURCE INDICATORS

News source indicators capture the market's reaction to news about the company, industry dynamics, and macroeconomic factors.

TABLE 4

NEWS SOURCE INDICATORS

Indicator	Reason for Use	Formula

Sentiment Analysis	Gauges market sentiment from news articles	-
News Volume	Measures the number of news articles published	Count of news articles
Event Impact	Analyzes the impact of specific events (e.g., earnings reports)	

Table 4

4. DEEP LEARNING MODELS

To illustrate how a hybrid deep learning model combining a convolutional neural network (CNN), a long short-term memory (LSTM) network, and natural language processing (NLP) can predict Nvidia's stock price and identify potential asset bubbles, here is an illustration of the model's structure.

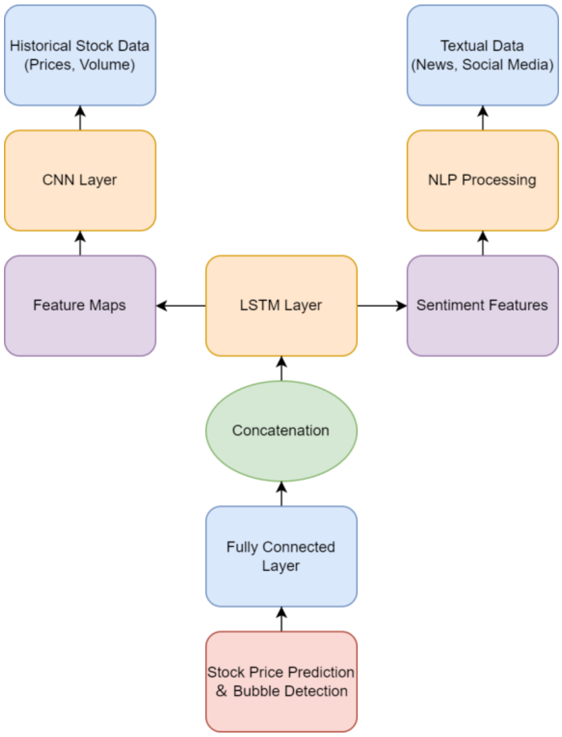

FIGURE 1. A hybrid deep learning model combining convolutional neural networks (CNN), long short-term memory (LSTM) networks, and natural language processing (NLP) was used to predict Nvidia's stock price and identify potential asset bubbles.

5. TRAINING AND EVALUATION

A. TRAINING

Hyperparameter Tuning: Discuss the process of selecting optimal hyperparameters such as learning rate, batch size, epochs, and optimizer. Describe any grid search or random search techniques used for tuning.

Training Process: Provide details about the training loop, including forward propagation, loss calculation (using loss functions such as MSE or binary cross entropy), backpropagation, and weight updates. Mention early stopping criteria to prevent overfitting.

Evaluation Metrics: Explain the evaluation metrics used to measure model performance. For regression tasks (stock price prediction), metrics such as mean absolute error (MAE), mean squared error (MSE), and R-squared should be used. For classification tasks (bubble detection), metrics such as accuracy, precision, recall, F1 score, and AUC-ROC should be used.

B. Experimental Setup

Hardware and Software Configuration: Detail the computing resources used. Mention deep learning frameworks and data processing libraries.

6. RESULTS

A. Model performance

Stock price prediction: Provide quantitative results for the stock price prediction task. Present results using MAE, MSE, RMSE, and R-squared metrics. Include visualizations comparing predicted and actual stock prices on the test set[2].

Bubble detection: Report classification accuracy, precision, recall, F1 score, and AUC-ROC for the bubble detection task. Visualize ROC curves and precision-recall curves.

B. Comparative Analysis

Baseline Models: Compare the performance of the hybrid model with a baseline model or a traditional machine learning model. Discuss how each model performs relative to the hybrid model.

Ablation Study: Perform an ablation study by removing components to understand the contribution of each part of the hybrid model.

7. DISCUSSION

A. Interpretation of Results

Effectiveness of the Hybrid Model: Discuss the overall effectiveness of the hybrid model in predicting stock prices and detecting bubbles. Highlight strengths such as capturing complex patterns and weaknesses such as overfitting to noise.

Role of Sentiment and News Data: Discuss the impact of incorporating sentiment analysis and news volume on the model's predictive power. Evaluate how well sentiment features captured market sentiment.

B. Implications for Financial Markets

Practical Applications: Discuss potential applications for traders, investors, and financial analysts. Explain how this model can aid in decision-making processes, risk management, and market analysis.

C. Limitations and Challenges

Data Quality and Availability: Discuss challenges related to data quality, such as inconsistencies in historical data, incomplete news datasets, or biased sentiment analysis.

Model Generalizability: Address the limitations of applying this model to other stocks or markets. Discuss potential overfitting and the need for model adaptation.

D. Future Work

Model Improvements: Suggest future research directions, such as using more advanced NLP models, incorporating additional market features, or applying reinforcement learning for trading strategies[2].

Broader Application: Consider applying the model to other sectors beyond technology or exploring cross-market interactions. Discuss the potential for real-time prediction and automated trading systems.

8. CONCLUSION

A. Summary of Findings

Recap the study's objectives, methodology, and key findings. Emphasize the hybrid model's success in capturing complex relationships in stock price movements and identifying asset bubbles.

B. Contributions

Highlight the novel contributions of this research, such as integrating CNN, LSTM, and sentiment analysis for stock prediction and bubble detection.

C. Practical Implications

Reiterate the potential benefits for investors, analysts, and financial institutions. Mention the potential for this model to enhance decision-making and risk management in financial markets.

D. Future Directions

Encourage further research into enhancing model accuracy, exploring different asset classes, and implementing real-time applications.

9. REFERENCE

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