Predicting Market Crash with LSTM Networks to Empower Smarter Financial Decisions

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ABSTRACT

A significant number of American households continue to rely on traditional savings accounts as their main financial savings method. Despite the availability of high-yield savings accounts offering substantially higher interest rates, many individuals remain hesitant to transition due to lack of information and concerns about market unpredictability. This over-reliance on traditional savings exposes their finances to the silent erosion of inflation, gradually diminishing the value of their savings over time. This project addresses these concerns by leveraging the predictive capabilities of Long Short-Term Memory (LSTM) networks to analyze historical stock market data and identify patterns that could signal potential market downturns. By integrating data sourced from the New York Stock Exchange (NYSE) through the Yahoo Finance API libraries, the model is specifically designed to provide actionable insights and strategies that mitigate the fear of market volatility and empower individuals to make informed investment decisions. The technical framework of the project employs advanced tools and methodologies. Neural network development is carried out using Python alongside TensorFlow and Keras, while data pre-processing, analysis, and visualization are conducted with Pandas, NumPy, Matplotlib, and Seaborn. The comprehensive approach enables the project to process large datasets efficiently, uncover trends, and generate precise market predictions. By providing accurate forecasts and highlighting potential risks, this project aims to guide people toward more profitable financial strategies, moving beyond the limitations of low-yield savings accounts. Ultimately, it seeks to help people safeguard their financial well-being while enabling the growth of their wealth through better-informed, data-driven investment choices.

1. Introduction

Economic uncertainty and inflation have long been significant challenges for people managing their personal finances. According to a report by the Consumer Federation of America, more than 50% of American households still rely on traditional savings accounts as their main financial strategy (1). While these accounts offer stability, their annual percentage yields (APYs) average just 0.35%, far below inflation rates that have recently ranged between 3.5% and 8% as shown in Figure 1 (2). This discrepancy erodes the purchasing power of savings over time, resulting in what economists describe as "inflationary loss." In practical terms, $10,000 saved in a low-yield account today may lose more than $400 in value in a single year under current inflationary trends.

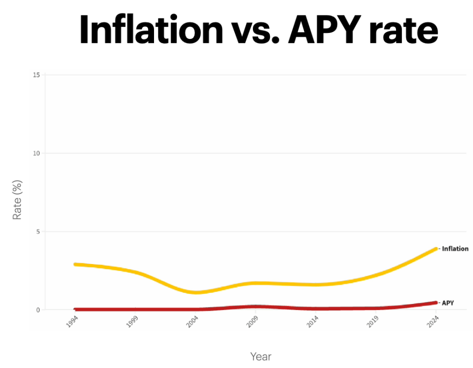

Fig. 1. Inflation vs APY

Despite the availability of investment vehicles such as high-yield savings accounts (averaging 4.25% APY) or diversified stock portfolios with historical annual returns of around 7% to 10%, hesitancy to engage with investment markets remains widespread. This reluctance is often attributed to a lack of knowledge and a fear of market volatility. According to a 2022

Gallup survey, 61% of Americans describe themselves as having little to no confidence in the stock market, leaving many financially unprepared to grow or even preserve their wealth (3).

The goal of this project is to explore how to accurately predict the volatile nature of the stock market. This research aims to empower consumers by providing them with better tools for financial decision-making. Ultimately, it seeks to optimize the use of personal finances through advanced machine learning techniques.

2. Related Work

Due to the U.S. stock market's significant influence on the global economy, it has become a focus of extensive research and analysis. One key area of interest for researchers today is exploring the potential to predict a crash with neural networks. Accurately predicting the stock market's rises and falls could boost public confidence in investing. In June 2024, a team from India released a report detailing the advantages of using a model that combines Graph Neural Networks (GNNs) and Long Short-Term Memory (LSTM) networks to effectively predict market crashes. They were able to predict crash detections with over 99% accuracy with their model, with the metrics for the model having high predictive accuracy and performance metrics compared to past approaches in modeling (8).

In August 2024, a study published in the *Scientific Journal of Informatics*, a research team from Indonesia, developed a model for early crash detection in the ASEAN-5 stock markets. Their experiments revealed that a Simple RNN architecture was best suited to handle the data characteristics, achieving a balanced accuracy of 62.6% for false alarm and hit rates, outperforming other models tested (9).

Similarly, in *Neural Computing & Applications*, another team using a hybrid GA-CNN model demonstrated that optimization methods for deep learning techniques can be effectively applied to reliably monitor the stock market, with their model achieving 73.7% accuracy (10). Building on insights from these studies and our own experimentation, we have developed and tested several high-performing models utilizing machine learning, including LSTM which achieved the highest overall performance metrics.

Market volatility, characterized by unpredictable fluctuations, has historically deterred many people from investing. Financial risk often poses significant psychological barriers, with individuals tending to be more influenced by potential losses than by possible gains (4). Behavioral finance research also shows that people often exhibit loss aversion, where the psychological impact of a loss is approximately twice as powerful as the joy of a similar-sized gain (5). Addressing this fear requires tools that provide clarity, predict market movements, and enable informed decision-making. This project bridges the gap between financial literacy and actionable investment strategies by employing machine learning. By providing actionable insights and identifying potential risks, the project encourages users to move beyond low-yield savings accounts to more profitable investment opportunities. Ultimately, this tool aims to improve financial decision making by equipping individuals with data-driven insights. By empowering users to navigate the stock market with confidence, the project aims to foster economic stability, promote wealth growth, and reduce financial disparities caused by inflation and risk aversion. These benefits extend beyond individual gains, contributing to a more resilient economy where informed investments drive sustainable growth.

3. Proposed Methods

This project bridges the gap between financial literacy and actionable investment strategies by employing three machine learning models: linear regression, gated recurring units (GRU), and long short-term memory (LSTM) networks to predict the average closing price of stocks at 14 days. LSTM models, a type of recurrent neural network, excel in processing and predicting time series data, making them particularly suitable for stock market prediction tasks. By analyzing historical stock market patterns, LSTM networks can capture short- and long-term dependencies, helping to identify trends and patterns indicative of potential market crashes.

LSTM was chosen as the primary model due to its ability to effectively capture sequential dependencies in financial data, which is essential to predict market movements. GRU and Linear Regression models were included for comparative analysis to evaluate the benefits of using more advanced techniques in stock price forecasting.

The methodology combines data-driven feature engineering and robust preprocessing to create a framework suitable for time-series prediction. A sliding window approach was used, where sequences of 60 days of historical stock prices serve as input to forecast the 14-day average. The following subsections detail the data collection process, the preprocessing pipeline, and model-specific implementations.

3.1. Data Collection

To achieve the objectives of this study, historical stock market data was collected from Yahoo Finance API, which provides access to comprehensive datasets from the New York Stock Exchange (NYSE), the largest financial market in the world. This dataset includes years of stock prices and trading volumes, offering a solid foundation for time series analysis. By analyzing historical stock market patterns, the project aims to identify trends and anomalies indicative of potential market crashes, enabling the development of a predictive model to forecast future price movements.

Data preparation involved leveraging Python libraries such as Pandas and NumPy to clean and format the data. Feature engineering was applied to improve the predictive capacity of the models by incorporating indicators such as simple moving averages (SMA), relative strength index (RSI), and daily returns. These features provide crucial insights into stock trends and volatility, enabling the model to capture complex market dynamics.

To establish baseline performance, the study first employed linear regression and GRU models. These methods offer insights into the relative performance of simpler and moderately complex models. Subsequently, LSTM networks were used as the primary model due to their proven ability to process sequential data and capture both short- and long-term dependencies, making them particularly suited for uncovering intricate patterns in stock price behavior.

3.2. *Preprocessing*

Preprocessing was a critical step in ensuring that the data were suitable for machine learning models. This stage involved several key processes:

- Data Cleaning and Handling Missing Values: Missing values often arise from features such as moving averages or RSI at the start of the dataset or from days when the stock market is closed (e.g., weekends and holidays). These gaps were addressed by replacing missing values with zeros to maintain the consistency of the dataset.
- Normalization: The dataset was scaled using the MinMaxScaler to normalize all features to a range between 0 and 1. This ensures that no single feature disproportionately influences the model's learning process.
- Feature Engineering: Key features were derived and used to train the models, each contributing unique insights:
  - Closing Price: The final stock price at the end of the trading day, representing a core performance indicator.
  - Volume: The total number of shares traded during the day, which reflects investor activity.
  - SMA_10 and SMA_50: Simple moving averages calculated over 10 and 50 days, respectively, to identify short- and long-term trends.
  - RSI_14: The 14-day Relative Strength Index, a momentum indicator predicting potential reversals.
  - Daily Returns: The percentage change in closing price from one day to the next, quantifying stock volatility.
  - P/E Ratio: The price-to-earnings ratio, a valuation metric comparing stock price to earnings per share.
  - Bollinger Band Upper: The upper boundary of Bollinger Bands, calculated as the 20-day simple moving average (SMA_20) plus two standard deviations of the last 20 prices, used to identify potential overbought levels.
  - Bollinger Band Lower: The lower boundary of Bollinger Bands, calculated as the 20-day simple moving average (SMA_20) minus two standard deviations of the last 20 prices, used to identify potential oversold levels.
- Data Splitting: The dataset was divided into training and testing subsets, with 80% allocated to training and 20% for testing. This split ensures that the model learns from historical data and is evaluated on unseen data.
- Sliding Window: A 150-day sliding window was used to create sequential datasets, allowing the LSTM model to learn patterns effectively. The model was trained to predict the next 14 values based on the previous 150 days of data. This method helps the model capture temporal dependencies in the data and improve its forecasting capabilities.

3.3. *Linear Regression Model*

Linear regression was selected as a baseline model to assess the predictive power of simpler, traditional approaches before advancing to more complex neural networks. Despite its simplicity, linear regression can offer valuable insights into stock price trends, particularly in capturing linear relationships between features such as moving averages, daily returns, and volume. The model is straightforward to implement and provides a clear interpretation of the relationship between the input features and the target variable, making it an ideal starting point for stock price prediction. By assuming a linear relationship, this method offers a useful benchmark to understand the basic predictive capabilities of stock market data before applying more complex models.

For the linear regression model, we used the same set of features as the other models to ensure consistency in the analysis. This included technical indicators such as moving averages, volume, RSI, and others. By evaluating its performance, we can better understand how much predictive accuracy can be gained by transitioning to more sophisticated models like GRU and LSTM, which are designed to capture long-term dependencies and more intricate patterns in time series data.

3.4. *GRU Model*

The GRU model was selected for its ability to efficiently handle sequential data, a crucial feature for time-series forecasting including stock market prediction. GRUs are able to capture dependencies over time, making them effective in modeling the temporal patterns found in stock prices. GRUs use fewer parameters than LSTM networks, which helps reduce computational complexity without sacrificing much predictive performance. This efficiency is especially valuable when processing large datasets, such as daily stock market data over extended periods. Additionally, GRUs offer a simpler architecture that reduces the likelihood of overfitting, which is important for maintaining the model's generalization capability when predicting future stock prices. Therefore, the GRU model was chosen to evaluate whether a lighter model could perform comparably to more complex architectures.

3.5. LSTM Model

LSTM networks are particularly effective for time-series forecasting tasks, such as predicting stock prices, because they are designed to capture both short-term fluctuations and long-term dependencies in sequential data. Stock prices often exhibit complex patterns that persist over time, making LSTM a strong choice for this type of prediction. The ability of LSTM to retain information through long sequences enables it to identify underlying trends and forecast future price movements based on historical data.

For this study, the LSTM model was trained on sequences of stock data spanning 150 days, with the goal of predicting the stock price for the next day. This method leverages temporal dependencies, allowing the model to consider past stock performance in its predictions. The sliding window approach was also used where each sequence represented historical data over a 150-day period, helping the model learn from both recent and longer-term stock trends. The sliding window not only captures the evolution of stock prices, but also allows for predictions over multiple steps into the future.

The training dataset was formatted into 892 sequences, each containing 150 time steps across several features. These sequences were used to teach the LSTM model to recognize patterns and dependencies in the data. The testing dataset consisted of 246 sequences with the same structure, enabling evaluation of the model's performance on unseen data to assess its predictive accuracy.

To ensure robustness in predictions, anomaly detection techniques, such as Z-scores and statistical thresholds, were applied. This worked to identify and exclude outliers that might skew the model's output. The LSTM's ability to handle noisy financial data, along with its focus on capturing both short-term variations and long-term market trends, makes it a powerful tool for stock market forecasting.

4. Experiments

The experiments were designed to evaluate the performance of the three models - Linear Regression, GRU, and LSTM - in predicting stocks' 14-day average closing price. Key metrics such as R-squared, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were calculated to provide a comprehensive evaluation of predictive accuracy and robustness.

Each model has a training sequence of 150-day historical stock prices and is validated on a test set representing the 14-day average closing prices. This approach ensured consistency across all models, enabling a direct comparison of their ability to capture market trends and predict short-term price movements accurately.

The experiments also included anomaly detection, focusing on significant market downturns (defined as drops exceeding 5% within a week) within a 12-month testing period. This secondary evaluation provided insights into the models' applicability as early warning systems for market risks, further underscoring their practical value.

4.1. Linear Regression Model

As expected, the Linear Regression model had the weakest performance among the three. It used 150 days of past data for predictions, consistent with neural network models, ensuring a fair comparison. The model achieved an R-squared value of 83.91%, which, while respectable, underscores the limitations of linear methods for complex, sequential data. Its MAE was 6.81, MSE was 80.54, and RMSE was 8.53. Performance declined steadily over the prediction days, reflecting the model's inability to capture long-term dependencies. On day 14, its metrics had deteriorated significantly, with an R-squared value of 69.96%, an MAE of 10.16, an MSE of 154.48, and an RMSE of 12.43. These results highlight the challenges of using linear models for extended forecasts yet provided a useful benchmark to measure the added value of neural network approaches.

4.2. GRU Model

The GRU model, using the same 150 days of past data, exhibited slightly lower performance metrics compared to LSTM but maintained strong predictive capabilities. Despite its basic architecture, the model leveraged early stopping to optimize training and prevent overfitting. It achieved an R-squared value of 83.17%, with an MAE of 7.14, MSE of 84.04, and RMSE of 8.88. As with the linear regression model, its performance dropped over the 14-day prediction horizon. On day 14, its R-squared value had fallen to 71.09%, with an MAE of 10.12, an MSE of 148.69, and an RMSE of 12.19. These results underscore the GRU model strength in capturing short- to medium-term trends, but also highlight its limitations in long-term predictions compared to the LSTM model.

4.3. LSTM Model

The LSTM model demonstrated the strongest predictive performance among the three models, achieving an overall R-squared value of 87.65%, indicating high explanatory power in predicting market trends. The error metrics were also favorable, with an MAE of 6.55, MSE of 63.56, and RMSE of 7.94. The

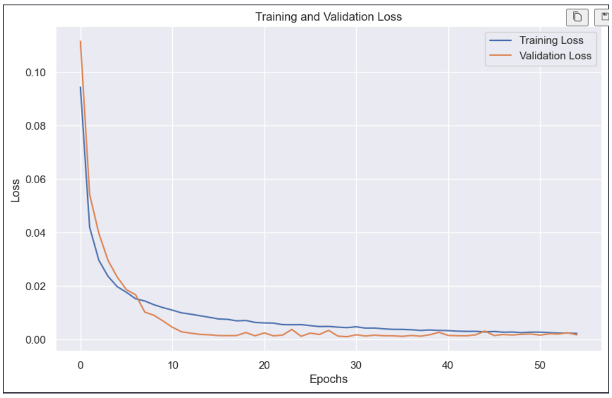

Fig. 2. LSTM Training and Validation Loss over Epochs

model flagged 93% of significant market downturns, highlighting its effectiveness as an early warning system. The LSTM model focused on maintaining accuracy across all 14 prediction days, displaying significantly better results compared to the other two models for the 14th-day metrics. On day 14, it delivered superior results compared to the other models, with an R-squared value of 88.68%, an MAE of 6.45, an MSE of 60.97, and an RMSE of 7.81. These metrics highlight the LSTM's ability to sustain performance and effectively capture long-term dependencies, making it the most reliable model for extended forecasts such as stock market prediction.

5. Results and Discussion

The three models were evaluated based on various metrics, including R-squared, MAE, MSE, and RMSE. The results highlight the performance differences between the models, emphasizing the strengths and weaknesses of each approach.

5.1. LSTM Model Loss

To monitor the optimization process, the training and validation loss were tracked over multiple epochs, as shown in Figure 2. The training loss consistently decreased over time, reflecting the model's ability to fit the training data. Similarly, the validation loss declined initially, indicating improved generalization to unseen data. However, a small divergence between the training and validation loss was observed as the training progressed, potentially signaling mild overfitting.

The LSTM model demonstrated stable learning behavior, with both training and validation loss exhibiting smooth convergence. The validation loss plateaued at a lower level than the training loss, indicating effective generalization. Despite slight fluctuations in validation loss, the gap between the two remained minimal, showcasing the model's robustness during training.

5.2. Model Performance Metrics

The performance of the models was evaluated using key metrics, including R-squared, MAE, MSE, and RMSE. Table 1 summarizes the results.

Table 1: Model Performance Metrics

Model	**R-squared (%)**	**MAE**	**MSE**	**RMSE**
LSTM	87.65	6.55	63.56	7.94
Linear Regression	83.91	6.81	80.54	8.53
GRU	83.17	7.14	84.04	8.88

The LSTM model achieved an average R-squared of 83.90%, showcasing strong predictive accuracy and its ability to model non-linear stock price trends. It reported higher errors on days 6 and 7, possibly due to increased market volatility. The linear regression model, with a comparable R-squared of 83.91%, excelled in capturing simpler trends, particularly during initial days, but its accuracy declined for more complex patterns. The GRU model, with an R-squared of 83.17%, performed well for short-term predictions but exhibited reduced robustness in long-term applications.

5.3. Model Strengths and Weaknesses

The LSTM model demonstrated superior handling of sequential dependencies and non-linear relationships, making it suitable for long-term stock price predictions. The GRU model, while efficient for short-term trends, struggled with long-term variability. In contrast, the linear regression model performed efficiently for simple and less volatile scenarios but failed to capture complex patterns over extended prediction horizons. These results suggest that model selection should align with the specific prediction requirements.

5.4. Comparison with Baseline Models

To evaluate the deep learning models, their performance was compared against the baseline linear regression model. As shown in Table 1, the LSTM and GRU provided higher accuracy for capturing non-linear trends, while the linear regression model excelled in simpler scenarios. Among the deep learning models, the LSTM consistently outperformed the GRU across all days, indicating its robustness for managing variability in stock prices.

The linear regression model remains a viable option for short-term predictions due to its computational simplicity. However, the LSTM and GRU are better suited for applications requiring adaptability to complex market conditions, with the LSTM being the most effective overall.

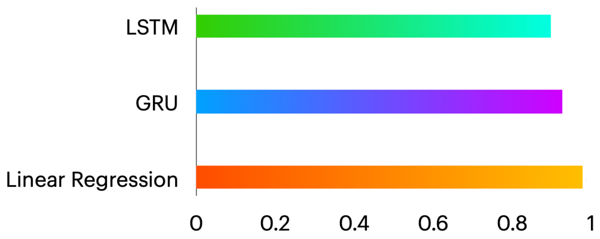

Fig. 3. R-squared at day 1

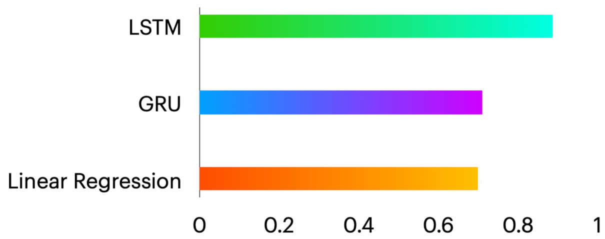

Fig. 4. R-squared at day 14

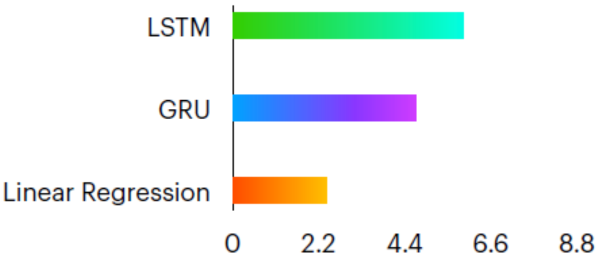

Fig. 5. MAE at day 1

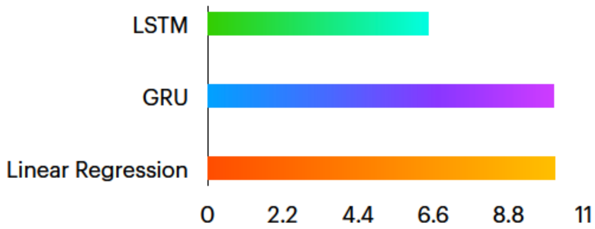

Fig. 6. MAE at day 14

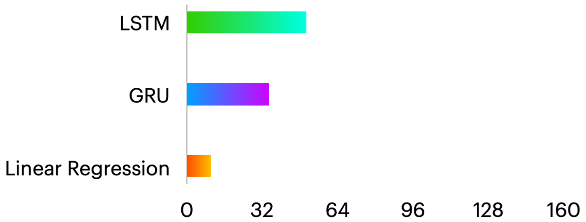

Fig. 7. MSE at day 1

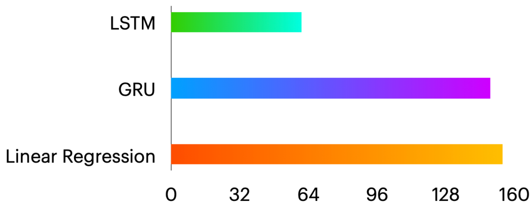

Fig. 8. MSE at day 14

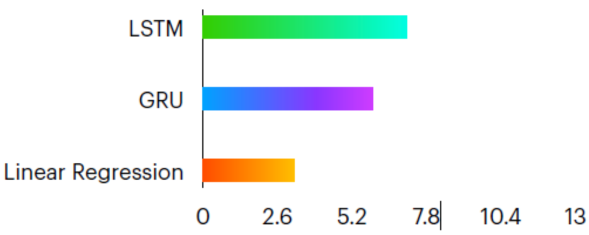

Fig. 9. RMSE at day 1

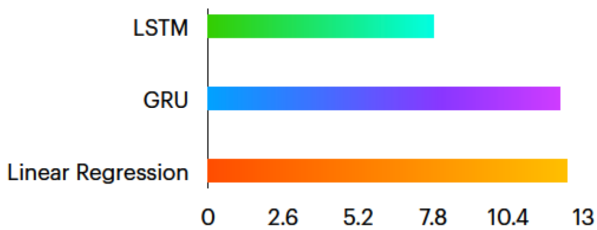

Fig. 10. RMSE at day 14

5.5. *Anomaly Detection*

The anomaly detection results, illustrated in Figure 11, highlight significant deviations in stock price trends. The blue line represents actual stock prices, while the red line depicts predicted prices. Anomalies were identified using Z-scores, with green upward-pointing triangles denoting ”good anomalies” (Z-scores > 0.8) and red downward-pointing triangles marking ”bad anomalies” (Z-scores < -0.8).

In early 2024, clusters of green triangles signal strong upward trends, indicating potential buying opportunities. By mid-2024, red triangles reflect price corrections, emphasizing

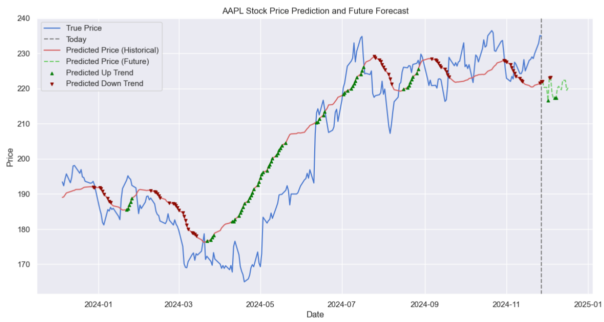

Fig. 11. LSTM Model Predictions with Anomaly Detection

the need for risk management during volatile periods. Post-November 2024, the forecast indicates a stable market environment, with fewer anomalies and reduced price variability.

The anomaly detection process enhances the model's utility by identifying growth opportunities (green anomalies) and market risks (red anomalies). However, limitations include reliance on static Z-score thresholds, which may overlook subtle changes, and occasional lags during extreme volatility. Future improvements could involve adaptive thresholds or ensemble techniques for enhanced detection accuracy.

6. Conclusion

The LSTM model demonstrated the strongest predictive capabilities, achieving the highest overall R-squared value of 87.65% while maintaining remarkable consistency throughout the 14-day prediction horizon. Its ability to sustain performance, with an R-squared value of 88.68% on day 14, highlights its effectiveness in capturing long-term dependencies and accurately predicting market trends. This consistency positions the LSTM model as a robust tool for predicting market crashes and guiding investment decisions.

However, certain limitations were identified. The model exhibited higher prediction errors during volatile periods and faced challenges in anomaly detection under extreme market conditions. The use of static Z-score thresholds may not fully capture nuanced market behaviors, limiting its adaptability to complex scenarios. Furthermore, the model has been specifically tuned for AAPL, as it aligns with industry standards, and requires further modifications to improve its robustness and achieve better accuracy across a wider range of stock options.

To address these limitations and expand the model's capabilities, several improvements have been identified. Future research could focus on integrating adaptive thresholds, ensemble methods, or hybrid models to enhance predictive and anomaly detection capabilities. Incorporating large language models (LLMs), such as ChatGPT and Grok, to analyze real-time events including news, politics, and social media could refine predictions further. A hybrid approach combining multiple methodologies and implementing a model selector to benchmark and choose the best-performing model for specific stocks could improve prediction accuracy and flexibility. Introducing personalized strategies tailored to users' risk tolerance may also increase the model's relevance to individual investors, providing more customized trade suggestions.

These proposed enhancements would further elevate the model's adaptability, enabling it to provide more reliable predictions across varying market conditions and user preferences. With continued development, the LSTM model could become an even more powerful tool for making smarter, data-driven investment decisions.

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