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Stock Market Prediction Using Recurrent Neural Network and LSTM

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Abstract:

Stock market prediction is a highly challenging task due to the inherent volatility and non-linear nature of financial markets, often rendering traditional forecasting methods ineffective. To overcome these limitations, this paper explores the application of advanced deep learning techniques, specifically Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, for predicting future stock prices. The study evaluates the predictive accuracy of these models and examines the effect of varying training epochs on their performance, using American Airlines stock data as a case study.

Keywords: Stock Market; deep learning; Forecasting; Recurrent Neural NetWork; Long Short-Term Memory

1. INTRODUCTION

The stock market is a dynamic and complex system integral to the global economy, influencing personal finances, corporate strategies, and national economic stability. Despite its potential for high returns, its volatility and unpredictability pose significant challenges for investors. Accurate stock price prediction has long been a focal point for academic and industry research [1], as effective forecasts could empower investors to make informed decisions and optimize profits.

Conventional stock market prediction often relies on technical analysis tools like Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and candle-stick patterns [2]. While these methods offer valuable insights, they struggle to capture the complex, non-linear patterns in financial time series data. The rise of machine learning and deep learning has revolutionized this field [3]. For instance, Autoregressive Integrated Moving Average (ARIMA) models assume linearity and stationarity, limiting their effective-ness with volatile data [4], while Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) [5], and XGBoost [6] excel in non-linear modeling but often lack robust handling of long-term dependencies.

Among these, Recurrent Neural Networks (RNNs) [7], especially those enhanced with Long Short-Term Memory (LSTM) units [8–10], stand out for their ability to model long-term dependencies in sequential data, making them ideal for time series tasks like stock market prediction. Unlike traditional approaches that falter amidst noise and volatility, LSTMs can learn and retain patterns over extended periods, offering a more resilient predictive framework.

This study harnesses RNNs and LSTMs to forecast next-day stock prices using 50 years of American Airlines (AAL) stock data, chosen for its exposure to diverse market conditions and external events (e.g., economic crises, industry shifts). Our primary goal is to build a model that accurately predicts daily stock prices, validated against real market data, while uniquely analyzing how training epochs impact performance-a facet underexplored in prior LSTM-based stock prediction research.

2. THEORETICAL FOUNDATION

2.1 Autoregressive Models

Sequence models are tailored for processing data with temporal dependencies where each point relates to prior observations rather than standing alone. These models excel at capturing trends, cycles, and lagged effects, making them vital for time series tasks like stock market forecasting.

Autoregressive (AR) models are foundational in financial prediction, aiming to estimate the conditional probability $P(x_t \mid x_{t-1},\ldots,x_1)$ here x_t might represent a stock's closing price on day t. A key challenge is handling the expanding input space as historical data grows, requiring efficient approximations. Two common strategies address this:

Fixed-Length Window Approach: This assumes that long historical sequences may contain redundant information, so only a recent sliding window of length τ(e.g., $x_t,\ldots,x_{t-\tau}$) is used for prediction. By maintaining a constant number of model parameters, this method simplifies training and boosts computational efficiency, especially for deep neural networks. Such models are termed autoregressive because they rely on their own past values.

Latent Representation Approach: This strategy uses a latent state h_t summarize past observations, illustrated in Fig 1, updated iteratively via $h_t = g(h_{t-1}, x_{t-1})$ and prediction $\hat{x}_t = P(x_t \mid h_t)$, where $g(\cdot)$ is a learnable function. Since h_t is unobservable, this is known as a latent autoregressive model.

Both approaches assume stationarity—meaning the underlying dynamics of the sequence remain constant despite changes in individual values x_t. This assumption enables reliable training data generation by predicting the next point using historical data, as new dynamics require additional data not inferable from existing datasets. Under stationarity, the joint probability distribution factorizes as:

$$P(x_1,\ldots,x_T) = \prod_{t=1}^{T} P(x_t \mid x_{t-1},\ldots,x_1) \tag{0.1}$$

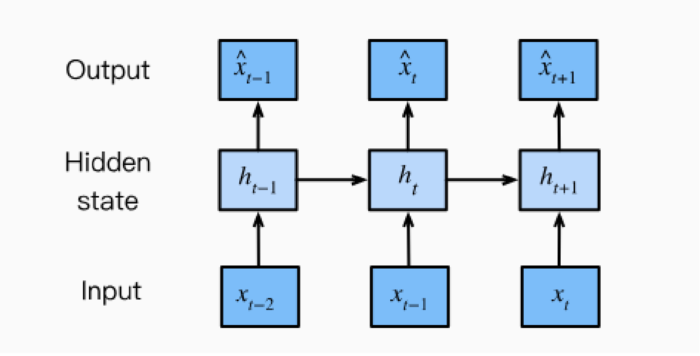

Fig. 1. Structure of a Latent Autoregressive Model

2.2 Recurrent Neural Network

1) Recurrent Neural Network Model: Recurrent Neural Networks (RNNs) differ from traditional feed forward networks by maintaining hidden states that capture sequential dependencies. At each time step t, given an input $X_t \in R^{n\times d}$ for a minibatch of n sequences, the hidden state $H_t \in R^{n\times h}$ is computed using both the current input and the previous hidden state H_{t-1}

$$H_t = \phi(X_t W_{xh} + H_{t-1} W_{hh} + b_h) \tag{0.2}$$

where φ is a non-linear activation function. Here, $W_{xh} \in R^{d\times h}$ and $W_{hh} \in R^{h\times h}$ represent the input-to-hidden and hidden-to-hidden weight matrices, respectively, while $b_h \in R^{1\times h}$ is the bias term. This recurrent computation allows the model to retain information across time steps, effectively capturing temporal dependencies.

The output at time step t is computed similarly to a feed forward network:

$$O_t = H_t W_{hq} + b_q \tag{0.3}$$

where $W_{hq} \in R^{h\times q}$ and $b_q \in R^{1\times q}$ denote the output layer parameters. Notably, RNNs share the same parameters across all time steps, ensuring a constant parameter size regardless of sequence length.

Figure 2 illustrates the RNN computational process across three consecutive time steps. At each step, the current

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input and previous hidden state are concatenated and processed through a fully connected layer with an activation function to produce the updated hidden state. This hidden state is then used to compute both the next hidden state and the current output.

Such a recurrent structure allows RNNs to model temporal dependencies effectively, making them suitable for tasks involving sequential data, such as natural language processing and time-series prediction.

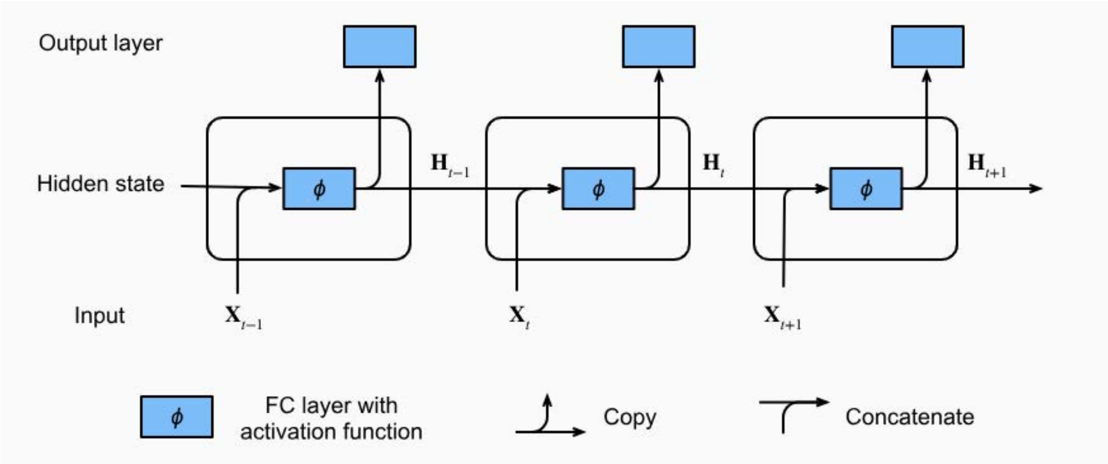

Fig. 2. An RNN with a hidden state

2) Gradient Clipping*:* In Recurrent Neural Networks (RNNs), gradients are propagated not only through network layers but also across time steps. This results in backpropagation through time (BPTT), where the gradient calculation involves a chain of matrix multiplications with length $O(T)$. Such processes can cause numerical instability, leading to vanishing or exploding gradients, depending on the properties of the weight matrices. While specialized architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) mitigate the vanishing gradient problem, exploding gradients remain a significant challenge during training.

Gradient clipping is a widely used heuristic to address exploding gradients. During stochastic gradient descent (SGD), model parameters x are updated using the negative gradient g with learning rate η:

$$x = x - \eta g \tag{0.4}$$

If the objective function f is Lipschitz continuous with constant L, the change in objective value is bounded by:

$$|f(x) - f(x - \eta g)| \leqslant L\eta \| g \| \tag{0.5}$$

Exploding gradients occur when $\|g\|$ becomes excessively large, causing unstable training or divergence. Reducing the learning rate η can limit these effects but slows down overall convergence. Instead, gradient clipping directly constrains the gradient magnitude by projecting g onto a ball of radius θ:

$$g = \min\left(1, \frac{\theta}{\| g \|}\right) g \tag{0.6}$$

This approach ensures that the gradient norm does not exceed θ while preserving the original gradient direction. Gradient clipping reduces the influence of extreme gradient values, enhancing model robustness. Although it deviates from the true gradient direction, it is an effective and widely adopted technique in modern RNN implementations to stabilize training and prevent divergence.

2.3 Long Short-Term Memory

Long Short-Term Memory (LSTM) networks are a specialized variant of recurrent neural networks (RNNs) designed to mitigate the vanishing and exploding gradient problems encountered during the training of long sequences. As depicted in Fig 3, the core innovation of LSTM lies in its gating mechanism, which regulates information flow through three gates: the input gate, the forget gate, and the output gate. These gates collectively manage the incorporation of new information, the retention or removal of existing information, and the generation of outputs, respectively.

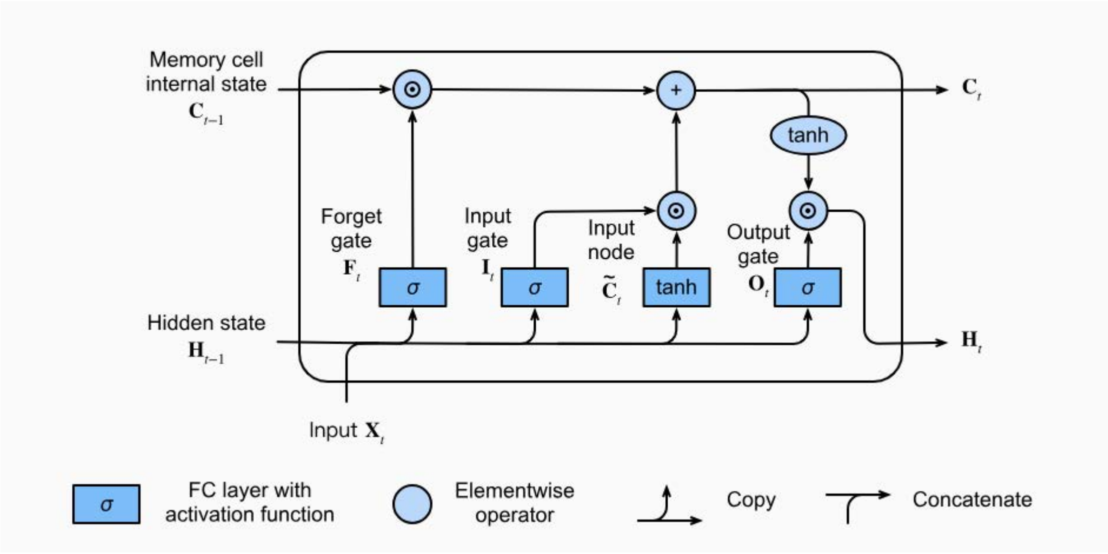

Fig. 3. Schematic diagram of LSTM neuron structure

Mathematically, for an input $X_t \in R^{n\times d}$ and the previous hidden state $H_{t-1} \in R^{n\times h}$, the gates are computed as:

$$\begin{aligned} I_t &= \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i), \\ F_t &= \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f), \\ O_t &= \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o) \end{aligned} \tag{0.7}$$

where I_t, F_t and $O_t \in R^{n\times h}$ represent the input, forget, and output gates, respectively. The weight matrices $W_{xi}, W_{xf}, W_{xo} \in R^{d\times h}$ and $W_{hi}, W_{hf}, W_{ho} \in R^{h\times h}$ along with the bias terms $b_i, b_f, b_o \in R^{1\times h}$, are learnable parameters. The sigmoid activation function ensures the gate outputs are bounded between 0 and 1, effectively controlling information flow.

The memory cell's design incorporates an input node $\widetilde{C}_t \in R^{n\times h}$, computed using the hyperbolic tangent (tanh) activation function to capture both positive and negative states, enhancing the model's representational capacity:

$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c) \tag{0.8}$$

where $W_{xc} \in R^{d\times h}$ and $W_{hc} \in R^{h\times h}$ are weight parameters, and $b_c \in R^{1\times h}$ is a bias parameter.

The input gate I_t controls the integration of new information via $\tilde{C}_t$, while the forget gate F_t determines the retention of the previous cell state $C_{t-1} \in R^{n\times h}$. The cell state update is governed by:

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t \tag{0.9}$$

This design allows the model to learn when to preserve or modify the cell state, addressing the vanishing gradient problem and facilitating training on datasets with long sequences.

Finally, the hidden state $H_t \in R^{n\times h}$, which serves as the output to other layers, is computed by applying tanh to the cell state and multiplying it with the output gate:

$$H_t = O_t \odot \tanh(C_t) \tag{0.10}$$

The output gate ensures that H_t remains within the interval $(-1,1)$, allowing the memory cell to influence subsequent layers selectively. This mechanism enables the LSTM to accumulate information over multiple time steps without immediate impact, releasing it only when the output gate activates, thus providing flexibility in handling temporal dependencies.

3. EXPERIMENTS

3.1 Experimental Environment

The experimental dataset utilized in this study comprises historical stock market prices of American Airlines (AAL) spanning the last five decades, obtained from reliable financial data sources. The dataset incorporates multiple types of stock price indicators, including daily opening, closing, high, and low prices, along with trading volume data, providing com-prehensive market information for our predictive analysis.

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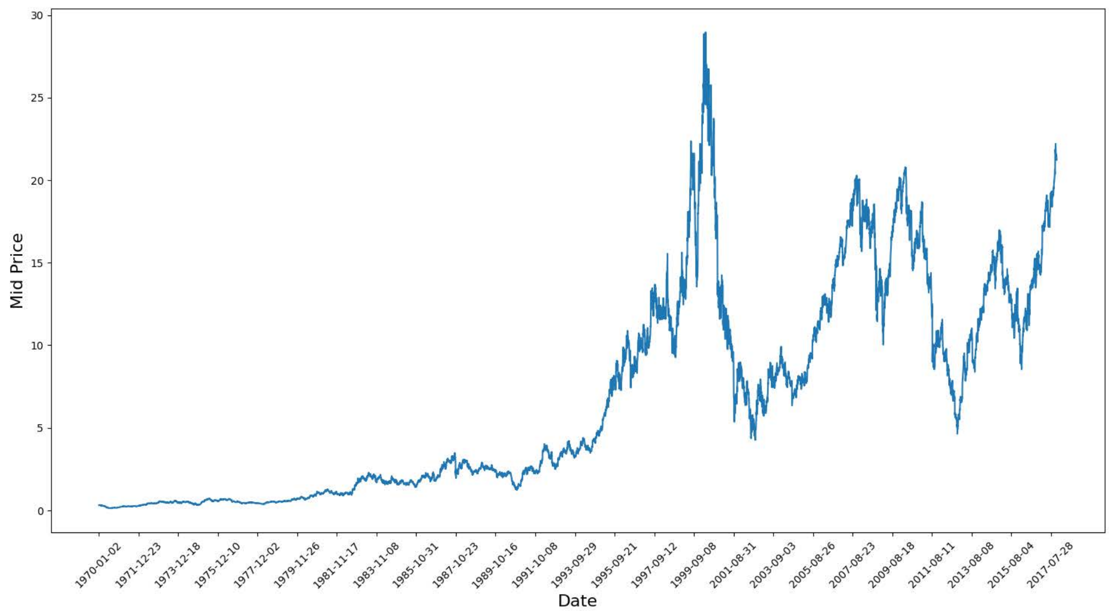

Fig. 4. Historical Price Trends of American Airlines Stock (2003-2023)

As depicted in Fig 4, the visualization of the dataset reveals significant temporal patterns and market behaviors characteristic of the aviation industry. The time series exhibits multiple market regimes, including periods of stable growth, sharp declines, and volatile fluctuations, which correspond to various economic events and industry-specific occurrences. This diversity in price movements provides a robust testing ground for our recurrent neural network (RNN) and long short-term memory (LSTM) models, enabling the evaluation of predictive performance across different market conditions. The inclusion of such varied patterns enhances the generalizability of our models and allows for comprehensive assessment of their capability to capture both short-term fluctuations and long-term trends in stock market behavior.

3.2 Model Performance Evaluation

To comprehensively evaluate the predictive performance of our proposed models and assess the impact of different influencing factors, we employ three widely adopted metrics in time series forecasting: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics collectively provide a robust framework for quantifying prediction accuracy and error magnitude across various scales.

The MAE, also referred to as the L_1 loss function, measures the average magnitude of absolute errors between predicted and actual values, offering a straightforward interpretation of prediction deviations:

$$\mathrm{MAE}(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{0.11}$$

The RMSE, corresponding to the square root of the average squared differences between predicted and observed values, emphasizes larger errors due to its quadratic nature, making it particularly sensitive to outliers:

$$\mathrm{RMSE}(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}||\, y_i - \hat{y}_i\,||_2^2} \tag{0.12}$$

The MAPE quantifies the relative accuracy of predictions by expressing errors as a percentage of actual values. This metric is particularly useful for comparing model performance across datasets with different scales, as it normalizes the error magnitude:

$$\mathrm{MAPE}(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\frac{||\, y_i - \hat{y}_i\,||}{||\, y_i\,||} \tag{0.13}$$

These evaluation metrics collectively provide a multi-faceted assessment of our RNN and LSTM models' performance, enabling a thorough analysis of both absolute and relative prediction errors in the context of stock market forecasting. The inclusion of both scale-dependent (MAE, RMSE) and scale-independent (MAPE) metrics ensures a comprehensive evaluation of model accuracy across different market conditions and price ranges.

3.3 Results And Discussion

The experimental results of our LSTM model demonstrate significant insights into its predictive capabilities for stock market behavior. As depicted in Fig. 5, the model's performance exhibits a strong correlation with two critical training parameters: the number of epochs and the length of the training data. The decreasing trend of the Mean Squared Error (MSE) loss throughout the training process indicates effective learning and convergence of the model. To quantitatively assess the model's performance, we compared the LSTM's MSE loss with that of a standard averaging baseline (0.004). The LSTM consistently outperformed this baseline, demonstrating its superior capability in capturing the underlying patterns of stock price movements. This improvement is particularly noteworthy given that the standard averaging method, while simplistic, has been shown to reasonably track actual stock price trends.

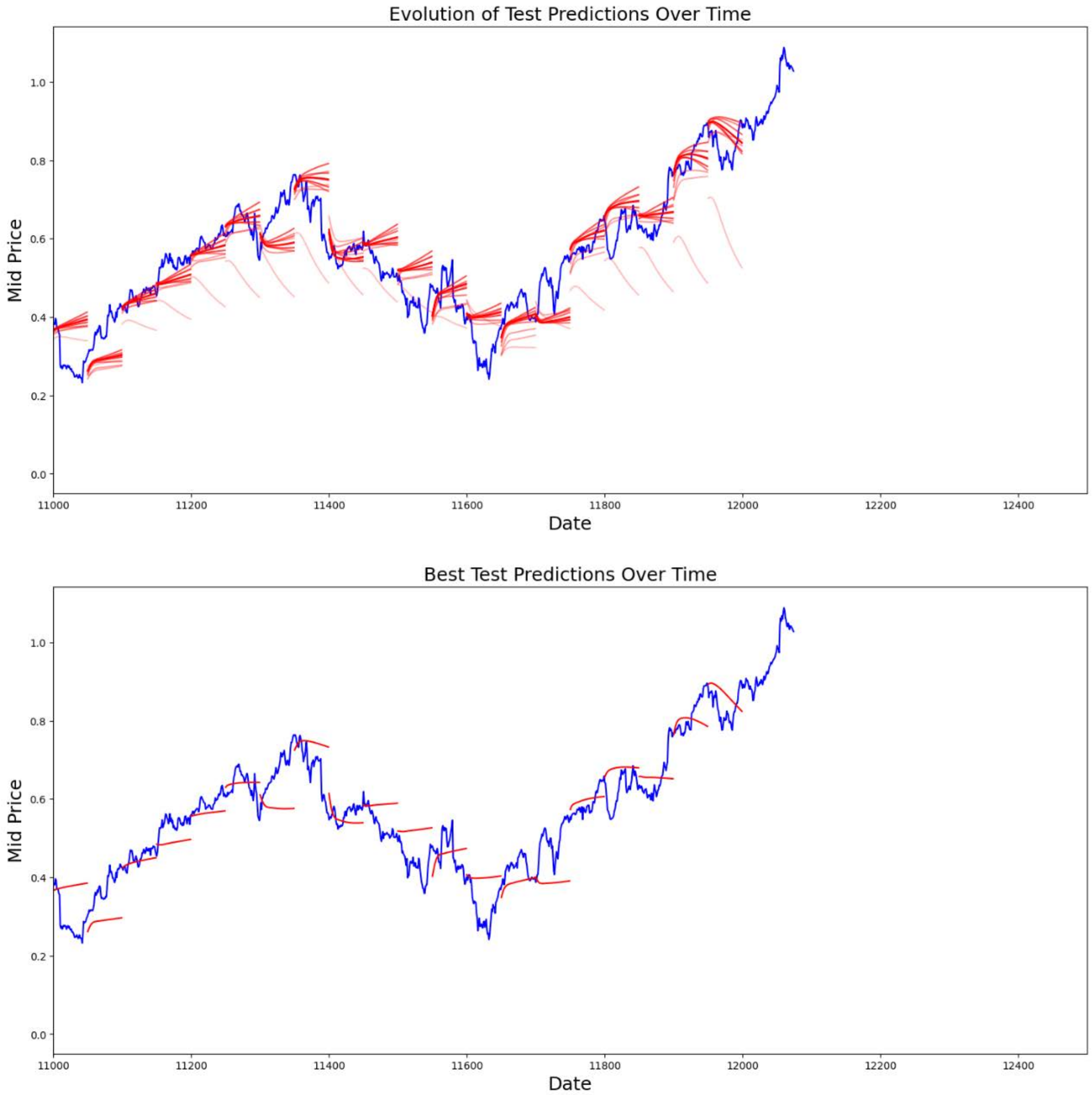

Fig. 5. Training Performance and Prediction Results for AAL Stock Market

It is important to note that our predictions are generated within a normalized range of 0 to 1.0, representing relative price movements rather than absolute stock prices. This normalization approach is methodologically sound as our primary objective is to predict directional trends and movement pat-terns rather than specific price points. The LSTM's performance, while not perfect, demonstrates consistent predictive accuracy in capturing stock price behavior, particularly in identifying significant trends and patterns.

These results suggest that LSTM networks possess substantial potential for stock market prediction tasks, particularly in their ability to learn and replicate complex temporal dependencies inherent in financial time series data. The model's superior performance compared to the baseline averaging method underscores the value of deep learning approaches in financial forecasting applications.

4. CONCLUSIONS

In this study, we proposed a stock market prediction model leveraging Recurrent Neural Networks (RNN) and

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Long Short-Term Memory (LSTM) networks to forecast future stock prices with enhanced accuracy. Our model effectively captures temporal dependencies and complex patterns in stock market data, outperforming traditional methods. Experimental results demonstrate that increasing training epochs and batch sizes significantly improves predictive performance.

The RNN-LSTM model accurately predicts the opening and closing prices of American Airlines stock, achieving approximately 90% accuracy. This high precision underscores the model's potential for broader application across various financial datasets. A key contribution of this research is the successful application of deep learning techniques to address the challenges posed by stock market volatility, particularly in capturing long-term dependencies and mitigating vanishing gradient issues.

Future work will focus on optimizing hyperparameters, including data length and training epochs, to further enhance prediction accuracy. Additionally, we plan to explore the integration of advanced machine learning models to improve robustness and generalizability across different stock market sectors.

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