# A STUDY ON DEEP LEARNING APPROACH TO PREDICT STOCK PRICES

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# ABSTRACT

The stock market, where shares of company ownership are traded, offers potential returns for investors, yet accurately predicting price movements remains challenging due to data volatility. A subfield of artificial intelligence called deep learning has great promise for the financial industry since it makes it possible to analyse big data sets and find intricate patterns that are challenging to identify manually. Methods like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) are notably adept at detecting patterns and variations in time-series data. Moreover, Artificial Neural Networks (ANNs) enhance the model’s understanding of complex relationships within stock data. By combining LSTM, CNN, and ANN, this approach demonstrates effectiveness in forecasting within the unpredictable environment of the stock market. The findings suggest that deep learning can offer more accurate, data-driven insights that benefit investors and financial institutions.

**KEYWORDS:** *Stock Market, Deep Learning, Financial Sector, Long Short-Term Memory, Convolutional Neural Network, Artificial Neural Network.*

# 1. INTRODUCTION:

Predicting stock prices is crucial in finance, offering valuable insights for investors, analysts, and financial institutions. Accurate predictions can guide better investment decisions and help manage financial risks, ultimately supporting a more stable and efficient market. However, stock price data is complex and highly volatile, making it challenging for traditional methods to achieve reliable accuracy.

Deep learning, a powerful area within artificial intelligence, has become essential for stock price prediction. By processing large datasets, deep learning models can identify patterns and trends within time-series data that are often missed by traditional methods. Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) are particularly effective for analyzing sequential stock data, while Artificial Neural Networks (ANN) excel at finding complex relationships within financial data. These models are designed to handle the non-linear, time-dependent fluctuations typical in stock data, making them valuable tools for forecasting.

This review analyzes existing deep-learning techniques for predicting stock prices, with a particular emphasis on LSTM, CNN, and ANN models. It further evaluates the effectiveness of these models using different datasets, incorporating metrics like accuracy, Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). By examining the advantages and disadvantages of each method, this review underscores the ability of deep learning to enhance forecasting precision and advocates for additional research to improve investment strategies and financial predictions.

**2. OBJECTIVES**

This article provides the information on following topics

* To investigate the use of deep learning models for predicting stock prices and analysing financial data.
* To evaluate the performance of models like LSTM, CNN, and ANN in forecasting stock price trends.
* To identify challenges and propose improvements in using deep learning techniques for financial forecasting.

# 4. RELATED WORK

A variety of deep learning approaches have been proposed to improve stock price prediction accuracy, addressing the complexity and non-linearity of financial data.

In [1], Ingle and Deshmukh introduced an Ensemble Deep Learning Framework (EDLF-DP) that combines TF-IDF features from financial news with stock market data. This framework achieved 85% accuracy in forecasting stock prices, highlighting the advantage of integrating sentiment analysis with deep learning for financial prediction.

Jiang in [2] provided an extensive review of deep learning applications in stock market prediction, categorizing previous research and emphasizing the need for reproducibility. Jiang pointed out that combining data types like historical prices, technical indicators, and news sentiment can improve model accuracy and suggested open-source resources for greater research collaboration.

In [3], Song presented AI-PREDIO, a weighted ensemble model that uses ANN, Gaussian Process Regression (GPR), and Classification and Regression Trees (CART) optimized through Cuckoo Search. This model, specifically applied to the construction sector, achieved low error rates, demonstrating its reliability for predicting volatile sector-specific financial data.

Shen and Shafiq proposed a comprehensive deep-learning model for short-term stock market trend prediction [4]. Using CNN and LSTM architectures, this model processed two years of Chinese market data and outperformed traditional machine learning models by capturing short-term fluctuations with greater accuracy.

Julian et al. in [5] explored stock price prediction through a multilayer perceptron (MLP) optimized with technical analysis indicators. They introduced the Mean Error to Mean Price Ratio as a metric for error tolerance, achieving an R-squared score of 0.995, which underscores the MLP model’s strength for technical analysis-based forecasting.

Rizvi and Khalid compared three deep learning models—MLP, LSTM, and GRU—for predicting Apple Inc. stock prices [6]. They found LSTM to be superior due to its memory retention capabilities, making it well-suited for capturing long-term dependencies in high-value markets.

Hu, Zhao, and Khushi [7] surveyed deep learning applications in Forex and stock market prediction, examining models such as CNN, LSTM, DNN, and Reinforcement Learning. Their review concluded that DNNs, when combined with other models, often outperformed standalone LSTMs, emphasizing the value of hybrid architectures in financial forecasting.

In [8], Mukherjee et al. compared CNN and ANN models on the National Stock Exchange (NSE) and found CNN to have an accuracy of 98.92%, particularly excelling during the volatile COVID-19 period. This study demonstrated CNN’s effectiveness in handling time-series data during high volatility.

Jing et al. introduced a hybrid model integrating CNN and LSTM with investor sentiment analysis [9]. Their approach improved stock price prediction accuracy by leveraging both technical indicators and sentiment data, highlighting the effectiveness of hybrid models in capturing nuanced financial trends.

Mehtab and Sen in [10] introduced a hybrid model that combines CNN and LSTM for the purpose of predicting stock prices, emphasizing the complementary strengths of CNN in feature extraction and LSTM in time-series analysis. Their approach demonstrated superior predictive accuracy with lower Mean Squared Error (MSE) and Root Mean Square Error (RMSE), surpassing conventional methods.

Bathla combined LSTM with Support Vector Regression (SVR) to enhance stock price prediction accuracy in [11]. This hybrid approach allowed for more precise forecasting by combining LSTM’s ability to capture temporal dependencies with SVR’s strength in regression tasks.

In [12], Goyal explored financial time series forecasting using deep learning. The study highlighted how deep learning models can support better investment decisions by analyzing historical price trends, with a focus on enhancing long-term investment strategies.

Prata et al. in [13] evaluated the performance of CNN and RNN models for stock price trend prediction using limit order book (LOB) data. They demonstrated that CNNs and RNNs could effectively capture complex patterns within LOB data, providing a benchmark for deep learning in financial forecasting.

Yang, Wang, and Wang proposed a model using LSTM and GRU for anomaly detection in stock prices [14]. Their framework successfully identified abnormal stock price patterns, demonstrating the potential of deep learning in financial anomaly detection.

In [15], Alkhatib et al. introduced an active deep-learning approach for stock price forecasting. By selectively sampling informative data points, the model improved both accuracy and efficiency, highlighting the effectiveness of active learning techniques for enhancing stock prediction models.

# 5. METHODOLOGY

5.1 Problem Definition:

The main objective is to enhance the precision of stock price predictions through deep learning approaches. These methods seek to offer forecasts that are more dependable, efficient, and accurate, facilitating improved decision-making. Deep learning architectures such as LSTM, CNN, and ANN excel in identifying intricate patterns and understanding time-dependent connections in stock price data, which is crucial for generating precise predictions.

5.2 Data Collection and Preprocessing:

Most models predicting stock prices are developed using past data, which is frequently sourced from financial platforms such as Yahoo Finance, Google Finance, and Bloomberg. This information generally comprises daily stock figures, including the opening and closing prices, as well as the highest and lowest prices alongside trading volumes. The process of data preprocessing is crucial for maintaining the integrity of the input data. This usually requires cleaning the dataset by dealing with missing values and outliers, which can be addressed through methods like interpolation or statistical imputation. Once the data is cleaned, it is commonly normalized with techniques like Min-Max scaling or Z-score normalization to ensure that all features fall within a comparable range, thus preventing any single feature from dominating the model. In the case of models such as LSTM and CNN, the data is arranged into fixed-length sequences, where each sequence reflects a collection of historical data meant to predict future stock prices.

5.3 Deep Learning Models:

Long Short-Term Model (LSTM): It is a specialized form of RNN designed to effectively process sequential data, making them ideal for tasks like predicting stock prices. They outperform traditional RNNs due to their ability to retain information for significantly longer periods. This capability is achieved through memory cells that include three gates: the input gate controls the entry of new data into the memory, the forget gate decides which previous information should be discarded, and the output gate governs which information is transmitted to the following step. The ability to remember and update information allows LSTMs to recognize important trends in stock prices over time, making them valuable for forecasting.

Convolutional Neural Network (CNN): These are often used for related image tasks but are useful in working with time-series data such as stock prices. CNNs are very good at finding patterns in data, such as price trends in different layers of filters called convolutional layers. These filters look at small sections of data and can pick up on the features or peaks and troughs in the stock prices. The data size is reduced with important features remaining in the pooling layers after the convolutional layers. All information the fully connected layer receives from previous layers is combined for a final prediction. In the CNNs, useful features are automatically detected in the stock price data, which helps make precise predictions. The below Fig.1 represents the working of CNN.



Fig. 1: CNN Architecture

Artificial Neural Network (ANN): It is structured with layers of interconnected nodes, which mimic the functioning of the human brain. Each node receives an input, processes it, and passes the output to the next layer. The standard structure of an artificial neural network (ANN) consists of three primary layers: the input layer, where the network takes in data; the hidden layers, where it identifies patterns and relationships within the data; and the output layer, where it generates the final prediction. The network enhances its performance over time through a method known as backpropagation, which modifies the connections between nodes based on errors encountered. In stock price forecasting, ANNs analyse the relationship between past prices, trading volumes, and various market elements, allowing them to predict future stock prices accurately. The below Fig.2 shows the basic structure of the ANN model.



 Fig.2: ANN Architecture

Hybrid Model (CNN-LSTM): This model integrates the advantages of both CNN and LSTM to enhance stock price forecasting. Initially, CNN is employed to identify significant features from the raw stock data, enabling the model to recognize essential trends and patterns. Subsequently, LSTM is utilized to grasp the sequential and temporal relationships among these features. The CNN layers detect localized patterns within the data, whereas the LSTM layers capture extended trends over time. By merging CNN’s feature extraction capability with LSTM’s understanding of temporal dependencies, the combined model elevates overall prediction accuracy, making it especially effective for stock price forecasting.

5.4 Model Training and Evaluation:

Deep learning models for stock price prediction involve splitting the dataset into training, validation, and testing sets. The training set is used to build the model, while the validation set helps adjust hyperparameters and avoid overfitting, which occurs when the model excels on training data but struggles with new data. Methods like dropout and L2 regularization are applied to maintain simplicity and generalization.

Model performance is assessed using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R²), which indicate prediction accuracy and explain variability. Cross-validation ensures the model performs consistently well on unseen data. The below Fig.2 compares the performance of six deep learning models using R-squared, RMSE, and MAE. The CNN model generally outperforms the others, while the ANN model has the lowest performance.

Fig. 2: Performance Metrics comparison of deep learning models

5.5 Challenges and Limitations:

Although the results are encouraging, using deep learning to predict stock prices presents numerous obstacles. The stock market experiences significant volatility, and external influences like geopolitical incidents or unexpected economic changes can significantly impact stock prices, complicating the accuracy of predictions. Furthermore, stock price data is often noisy, and the task of extracting meaningful patterns from this data remains complex. Overfitting presents a considerable challenge, as deep learning models often learn the training data by heart instead of effectively generalizing to unseen data. Moreover, models trained on historical data may struggle to predict sudden market shifts or unforeseen events that fall outside the training data distribution.

**6. RESULTS AND DISCUSSION**

**6.1 Model Performance Comparison**

The models were evaluated on multiple datasets containing historical stock prices from platforms like Yahoo Finance. Each dataset was pre-processed to ensure consistency and accuracy before model training. The evaluation used metrics such as **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, and **R-squared (R²)** to quantify the accuracy and reliability of the predictions.

Figure 2 compares the performance of LSTM, CNN, ANN, and the hybrid CNN-LSTM model based on these metrics. The results revealed that:

1. **LSTM** demonstrated superior performance in capturing long-term dependencies in sequential data, making it particularly effective for predicting gradual trends.
2. **CNN** excelled at extracting features from the data, making it adept at identifying localized patterns such as spikes or dips in stock prices.
3. **ANN** showed comparatively lower accuracy, likely due to its less specialized architecture for sequential data.
4. **Hybrid CNN-LSTM** emerged as the most effective model, combining CNN’s ability to detect patterns with LSTM’s strength in understanding time-series dependencies.

**6.2 Discussion**

The results highlight the effectiveness of deep learning approaches in predicting stock prices, with the hybrid CNN-LSTM model showing the best overall performance. This aligns with previous research, which emphasizes the advantages of combining models to leverage their unique strengths.

1. **Strengths of Deep Learning Models**
	* **LSTM**’s ability to retain long-term dependencies is valuable in forecasting extended trends in stock prices, making it suitable for long-term investors.
	* **CNN**’s feature extraction capabilities are ideal for identifying short-term patterns, making it a preferred choice for traders who rely on technical analysis.
	* **Hybrid models** maximize prediction accuracy by combining the strengths of different architectures, offering a more balanced approach to stock price forecasting.
2. **Challenges Encountered**
	* **Data Volatility**: High fluctuations in stock prices during economic downturns or political instability led to reduced model accuracy. The models struggled to predict sudden, unpredictable events such as market crashes.
	* **Overfitting**: Deep learning models, particularly ANN, were prone to overfitting during training. Techniques such as dropout and L2 regularization were implemented to mitigate this issue.
	* **Data Quality**: The presence of missing values or anomalies required extensive preprocessing. While interpolation and imputation helped, noise in the data sometimes affected prediction quality.
3. **Insights and Practical Implications**
	* Deep learning models, especially the hybrid CNN-LSTM, provide actionable insights for investors and financial analysts, enabling more informed decision-making.
	* The models' ability to process and analyze large datasets makes them a valuable tool for predicting price trends and managing financial risks.

**6.3 Recommendations for Improvement**

Despite the promising results, there are areas for further research:

* **Incorporating Sentiment Analysis**: Combining market sentiment data with historical prices could enhance prediction accuracy, especially during volatile periods.
* **Dynamic Model Tuning**: Developing models that adapt to market changes in real-time could improve performance.
* **Hybrid Architectures**: Exploring combinations of CNN, LSTM, and other models like Gated Recurrent Units (GRU) or Transformer-based architectures may offer additional performance improvements.

# 7. CONCLUSION

This study examines how the advancements in deep learning methods have greatly enhanced the precision of stock price forecasts. These models are especially efficient because they can identify intricate patterns and understand the fundamental trends of stock market data. Despite challenges like overfitting and data quality issues, advancements in model training, regularization methods, and evaluation metrics have made these systems more reliable and robust. Future research should focus on enhancing these models, exploring new approaches for improved performance, and incorporating additional market-related factors and real-time data. With ongoing improvements, deep learning has the potential to transform stock price prediction, providing valuable insights for financial markets.

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